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Review

Sensing technologies for precision specialty crop production

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ABSTRACT

With the advances in electronic and information technologies, various sensing systems have been developed for specialty crop production around the world. Accurate information concerning the spatial variability within fields is very important for precision farming of specialty crops. However, this variability is affected by a variety of factors, including crop yield, soil properties and nutrients, crop nutrients, crop canopy volume and biomass, water content, and pest conditions (disease, weeds, and insects). These factors can be measured using diverse types of sensors and instruments such as field-based electronic sensors, spectroradiometers, machine vision, airborne multispectral and hyperspectral remote sensing, satellite imagery, thermal imaging, RFID, and machine olfaction system, among others. Sensing techniques for crop biomass detection, weed detection, soil properties and nutrients are most advanced and can provide the data required for site specific management. On the other hand, sensing techniques for diseases detection and characterization, as well as crop water status, are based on more complex interaction between plant and sensor, making them more difficult to implement in the field scale and more complex to interpret. This paper presents a review of these sensing technologies and discusses how they are used for precision agriculture and crop management, especially for specialty crops. Some of the challenges and considerations on the use of these sensors and technologies for specialty crop production are also discussed.

Contents

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1. Introduction

Specialty crops are facing increasing market pressures that threaten their long-term viability. In the U. S., high labor costs, uncertain labor pools, limited access to international markets, and increased competition could eliminate numerous specialty crop industries within the next 10 years (Burks et al., 2008). This situation can become a serious threat to the survival of rural communities and to food security.

The majority of specialty crop production enterprises rely on low-wage, seasonal and usually unskilled labor. Socio-economic research has shown that automation in many industrial sectors creates more job opportunities than it eliminates but in different professions. This results from the reduction of the availability of job vacancies for lower-skilled, and potentially unsafe production tasks, while creating opportunities for higher skilled and more specialized workers in jobs related to manufacturing, support, service, and finance — and industries that create innovative products or solutions, which in many cases leads to a more competitive market position.

The introduction of automation in crop production industries concerns tools and technologies that can improve efficiency and product quality and also reduce the environmental impact which is an unwanted side-effect of processing (http://www.csrees.usda.gov/nea/ag_systems/pdfs/specialty_crops_engineering.pdf). Eventually, these technologies need the extensive use of sensors to be able to perform these tasks. These sensor-intensive technologies include:

(1) Novel technologies for controlling the applications of chemicals and nutrients in a way that improves efficiency, reduces cost, improves worker safety, and reduces the impact on the environment. These technologies require extensive use of sensors.
(2) Operations enhanced by the use of non-contact sensors in mechatronic and robotic solutions, to increase productivity and subsequently minimize labor cost. Examples include fruit thinning, pruning, spraying, and harvesting as appropriate.
(3) Autonomous navigation systems that can be applied to different agricultural operations like harvesting, spraying and utility vehicles. These operations need a number of crop sensors in order to function in a fashion that is sensitive to local crop conditions.
(4) Precision agriculture involves sensor technologies for yield mapping and prediction, soil sensing, nutrient and pesticide application, irrigation control, etc. Precision agriculture makes extensive use of sensors in order to identify proper targets and needs of crops for applying locally varying doses of chemicals.

(5) The monitoring of diseases and pests and scouting is based on various approaches including a number of sensor technologies like space-based or airborne remote sensing, and ground-based systems using proximal non contact sensing.

Recent and ongoing sensor developments allow growers to closely monitor and control many aspects of crop production. Remote and local sensors or sensor networks can be applied to monitor plant nutrient and moisture needs, soil conditions, and plant health (including insect and disease detection). Precision agriculture is based on such information intensive sources and attempts to address the site-specific needs with spatially variable application. To establish a reliable and wide foundation for precision agriculture, there is a desperate need for data with high spatial resolution, wide thematic range and high thematic resolution. The described sensors have been developed exactly for this purpose: to fulfill that need for data.

With the advances of electronic and information technologies, various sensing systems have been developed for specialty crop production around the world. This paper reviews the sensing technologies that have been developed and used for implementing precision farming for specialty crops. The information needed for precision crop management includes crop yield, soil properties and nutrients, crop nutrients, crop canopy volume and biomass, water content, and pest conditions (disease, weeds, and insects). The methods and technologies used for detecting crop information include field electronic sensors, spectroradiometers, machine vision, airborne multispectral and hyperspectral remote sensing, satellite imagery, and thermal imaging, among others. This paper presents these sensing technologies in seven sections and discusses how they are used for precision agriculture and crop management, especially for specialty crops. Some of the challenges and considerations on the use of these sensors and technologies for specialty crop production are also discussed.

2. Specialty crop yield mapping

2.1. High resolution remote sensing imagery

Crop yield is perhaps the most important piece of information for crop management in precision agriculture. It integrates the effects of various spatial variables such as soil properties, topography, plant population, fertilization, irrigation, and pest infestations. A yield map can therefore be an indispensable input for site-specific operations either by itself or in combination with other spatial information (Searcy et al., 1989). Despite the commercial availability and increased use of yield monitors, most of the harvesters are not equipped with them. Moreover, yield monitor data can only be used for after-season management, whereas some problems such as nutrient deficiencies, water stress, or pest infestations should be managed during the growing season. Remote sensing imagery obtained during the growing season has the potential not only for after-season management, but also for within-season management. Additionally, yield maps derived from remote sensing imagery can be used as an alternative when yield monitor data are not available.

Traditional satellite imagery has been used for yield estimation over large geographic areas, but this type of imagery has limited use for assessing the variation in yield within fields because of its coarse spatial resolution. Therefore, airborne multispectral and hyperspectral imagery and high resolution satellite imagery have been used for mapping within-field yield variability and other precision agriculture applications. Airborne multispectral imaging systems provide image data at fine spatial resolutions and at narrow spectral bands and have the real-time monitoring capability. Airborne multispectral imagery has been related to crop yields based on samples collected on field plots or in various sampling patterns (Richardson et al., 1990; Yang and Anderson, 1999; Shanahan et al., 2001; Leon et al., 2003; Inman et al., 2008). With the increased use of harvester-mounted yield monitors, intensive yield data can be collected from a field. The availability of both yield monitor data and remote sensing imagery allows the relations between yield and spectral image data to be evaluated more robustly and thoroughly than the use of limited numbers of yield samples. Many researchers have evaluated the relationships between yield monitor data and airborne multispectral imagery (Senay et al., 1998; GopalaPillai and Tian, 1999; Yang et al., 2000; Yang and Everitt, 2002; Dobermann and Ping, 2004).

Hyperspectral imagery contains tens to hundreds of narrow bands and provides additional information that multispectral data may have missed. These almost continuous spectral data have the potential for better differentiation and estimation of biophysical attributes for some applications. Airborne hyperspectral imagery has been evaluated for estimating crop yields (Goel et al., 2003; Yang et al., 2004a,b; Zarco-Tejada et al., 2005; Yang et al., 2007). The commercial availability of high resolution satellite sensors such as IKONOS, QuickBird, and SPOT 5 has opened up new opportunities for mapping within-field variability. These satellite sensors have significantly narrowed the gap in spatial resolution between satellite and airborne imagery. IKONOS and QuickBird imagery has been evaluated for assessing crop yields (Chang et al., 2003; Dobermann and Ping, 2004; Yang et al., 2006a,b).

Vegetation indices (VIs) derived from the spectral bands in multispectral imagery have long been used to estimate crop yields (Tucker et al., 1980; Wiegand et al., 1991; Plant et al., 2000; Yang and Everitt, 2002). These VIs are usually formed from combinations of visible and near-infrared (NIR) wavebands. Two of the earliest and most widely used VIs are the simple NIR/Red ratio (Jordan, 1969) and the normalized difference vegetation index (NDVI) (Rouse et al., 1973). Another commonly used index is the soil-adjusted vegetation index (SAVI) (Huete, 1988). Many other VIs including band ratios such as NIR/Green and normalized differences such as the green NDVI have also been used for yield estimation (Yang et al., 2000, 2006a; Dobermann and Ping, 2004). In addition to VIs, yield has been directly related to all individual bands in multispectral imagery and to the principal components derived from the imagery using regression analysis to determine the amount of variability explained by the imagery (Chang et al., 2003).

In principle, all the VIs that have been developed based on multispectral data can be applied to hyperspectral data. However, multispectral data only have a few bands to use for calculating VIs, while hyperspectral data contain tens to hundreds of bands to choose from. Thus the number of VIs that can be derived from a hyperspectral image can be overwhelmingly large. Yang et al. (2004a) applied stepwise regression analysis on grain sorghum yield monitor data and 102-band airborne hyperspectral imagery to identify optimum band combinations for mapping yield variability. They also used principle components analysis and stepwise regression to select the significant principle components to account for the yield variability. To demonstrate the advantage of narrow hyperspectral bands over broad multispectral bands for yield estimation, Yang et al. (2004b) aggregated hyperspectral bands into Landsat-7 ETM+ sensor's four broad visible and NIR bands and found that the combinations of significant narrow bands explained more yield variability than the four broad bands. Zarco-Tejada et al. (2005) calculated a number of VIs using selected narrow bands from airborne hyperspectral imagery to estimate cotton yield. Yang et al. (2007) applied linear spectral unmixing techniques to 102-band hyperspectral images to derive plant cover fractions for mapping the variation in crop yield. The plant fraction images provided better r-values with yield than most of the 5151 possible narrow-band NDVIs derived from the 102-band hyperspectral images.

Remote sensing has been used for yield estimation for various annual crops, but only limited research has been conducted on yield estimation for specialty crops such as fruit trees and vegetables. Koller and Upadhyaya (2005a,b) examined the relationships between leaf area index (LAI) and a modified NDVI for processing tomatoes and used the LAI derived from aerial images and photosynthetically active radiation (PAR) to predict tomato yield. Their results showed that although the actual and predicted yield maps did not have a very high correlation, the two maps had similar yield patterns. Ye et al. (2007) used partial least squares (PLS) regression models to predict the yields of citrus trees from their canopy features obtained from airborne hyperspectral imagery as compared with vegetation indices and multiple linear regression models. Their results showed that vegetation indices and multispectral regression models failed to predict citrus yield, but PLS models successfully predicted citrus yield with R-squared values of 0.51 to 0.90. Ye et al. (2008) also examined the relationships between particular canopy features obtained from airborne multispectral images and the fruit yields of citrus trees and they found that mature leaves in canopies were more significantly correlated with fruit yield for the current growing season, while younger leaves were more significantly correlated with fruit yield for the following growing season. Yang et al. (2008) evaluate CIR aerial photography and field reflectance spectra for estimating cabbage physical parameters and their results show that both aerial photography and reflectance spectra can be used to extract cabbage plant growth and yield information.

It should be noted that the statistical models relating yield to spectral bands or vegetation indices are generally developed based on the data collected from specific fields at specific times of the growing season. These models may be valid for yield estimation for fields with similar growing conditions (i.e., crop variety, growing stages, fertilization, irrigation, and pest management). Obviously, if one or more growing conditions are significantly different, the models will not perform as well or even give erroneous results. Currently, commercial yield monitors are available for major crops such as grain and cotton, but there are not many commercial yield monitors for most specialty crops except a few crops (citrus, pistachio, and tomato) being in commercial or developmental stages. Airborne imagery in conjunction with ground sampling and statistical analysis can provide an alternative for yield mapping. Imagery acquired on different growth stages of a crop will provide some clues as to the optimal time periods for image acquisition for yield estimation. While accurate estimates of yield are not always possible during the season, yield patterns and within-field management zones identified from airborne multispectral and hyperspectral imagery can be very useful for both within-season and after-season management. Much research on remote sensing for yield estimation is needed to adapt the existing methods and develop new methods for specialty crops. Spectral measurements from crop canopy made at certain growing stages of the growing season can be used for yield estimation, but many other factors including weather, image availability and lack of user-friendly and reliable models present some of the challenges for the widespread use of remote sensing for yield estimation. Research has shown that hyperspectral imagery has some advantage over multispectral imagery for this application. However, more research is needed to compare different types of remote sensing imagery for their effectiveness, cost, and practicality.

2.2. Machine vision

Machine vision is based on digital images and tries to mimic human perception to provide information or input to systems that need it for application of site specific crop production. The most common application of machine vision is based on silicon sensors (CCD or CMOS arrays) that are sensitive to the range of 400–1000 nm. Within this group, color machine vision is most common, because of its low price and multitude of information contained in the color images. Color machine vision includes three wide spectral channels (approximately 150 nm FWHM), centered at the three basic colors, red (∼600 nm), green (∼550 nm) and blue (∼450 nm). Nevertheless, multispectral cameras employing specific bands have been used to enhance segmentation (Zandonadi et al., 2005). The main areas that color machine vision has been developed for precision farming include weed detection for site specific herbicides spraying, row detection for autonomous navigation and fruit detection for yield estimation or robotic harvesting.

Maybe the most acute problem with machine vision is the problem of color changes caused by variation in natural illumination, both in intensity and spectral content. Common practice when dealing with intensity changes is the use of color ratios, whereas changes in spectral content present more of a problem. Various methods have been proposed for image binarization when the intensity of the illumination varies (Onyango and Marchant, 2003; Granitto et al., 2005; Tian and Slaughter, 1998; Nieuwenhuizen et al., 2007). These methods are based on ratios between color channels, or indices like Excessive Green (EG) and Red minus Blue (RB), or the angular position of a pixel in a plane normal to the illumination vector in the R, G, and B coordinate space.

Spectral changes in the illumination can also be compensated when assumptions about the functional form of the illumination's spectral characteristics are made. Most of the activities in precision agriculture are performed outdoors under natural daylight. When natural sunlight is considered as the illumination source, it can be represented in a form whereby it is possible to derive a monochrome image that is invariant to illumination spectral changes (Marchant et al., 2004), from a 3-band color image.

Precision agriculture in orchards considers the tree as an individual production unit. In such an approach, sensing technologies are required in order to provide information about the status of each tree, regarding the nutrients, water status, fruit load and yield. The technology for nutrients and water status detection is similar for field crops. Nevertheless, yield estimation, as well as site specific (tree specific) handling often depends on the fruit load of the tree. Therefore, much effort has been invested in automatic fruit detection and yield estimation of fruits.

Some of the fruits have distinct color differences from the foliage and make them more distinguishable (for example mature oranges, red apples) and others have colors similar to that of the tree canopy, making them more difficult to detect (for example immature oranges and green apples). Color machine vision has been found useful for detection of Fuji apples (red in color) in the tree canopy when the color contrast is high (Bulanon et al., 2002). Multispectral imaging showed the potential for detecting immature green oranges (Kane and Lee, 2007). Hyperspectral imaging, along with morphological image processing was also shown to have good potential for detecting green apples in the tree canopy (Safren et al., 2007).

Occlusion is an obstacle to two-dimensional machine vision recognition of fruits and plants in natural outdoor scenes. The watershed algorithm was proved to be suitable to improve the recognition of occluded fruits in a tree canopy, as well as plant leaves (Safren et al., 2007; Lee and Slaughter, 2004).

2.3. Thermography

Thermal imaging has been also used for estimating the number of fruits in orchards and grooves (Stajnko et al., 2004; Wachs et al., 2009; Bulanon et al., 2008). The detection of the fruits is based on the assumption that their temperature differs significantly from the surroundings. This hypothesis is true in many cases, since the thermodynamic properties of fruits are different than those of the surrounding objects: both fruits and biomass consist mainly of water; but fruits' mass is usually larger than that of other biomass elements like leaves, making their transient thermodynamic response, and specifically the time constant of the transient response, significantly different. Nevertheless, the fruits' temperature is also affected by the intensity of the incident radiation, ambient temperature, relative humidity and wind speed.

Image processing algorithms are more effective in detecting the fruits when the contrast between fruits and surroundings is maximum. In an attempt to evaluate the best time for fruit detection, the thermal temporal variation in citrus canopy was analyzed (Bulanon et al., 2008). A relatively large temperature difference between fruit and canopy occurred from the afternoon, around 16:00, until midnight. This enhanced the fruit in the thermal images and facilitated fruit detection (Bulanon et al., 2008; Stajnko et al., 2004). Bulanon et al. (2008) employed a segmentation approach using the histogram tail method, which proved to be effective in discriminating the fruit from canopy especially when the temperature difference between leaves and fruits was large. An average true positive rate of 0.70 and a false positive rate of 0.06 were achieved. Since this success rate is marginal for robotic harvesting, thermal imaging was consequently fused with additional vision systems to improve the performance.

Stajnko et al. (2004) used the pseudocolor thermal image and color image processing tools to detect the fruits. In such an approach, the temperature information in the image is transformed to a color according to the chosen color mapping. The results of image processing may then depend on the color coding of the pseudocolor image. The number of apples automatically detected was highly correlated with the number of fruits manually counted in the images. Furthermore, the fruit diameter could also be evaluated from the thermal images, with better accuracy obtained when the fruits were ripe.

Fusion of multi-modal images (thermal and RGB) can enhance the detection accuracy of fruits (Bulanon et al., 2008; Wachs et al., 2009). A first step to fuse thermal with RGB images is to co-register the images. Automatic registration using a combination of a number of similarity measures proved to be superior than using each of the similarity measures alone (Wachs et al., 2009). This combination method finds the optimal transformation parameters for each pair of TIR and RGB images to be registered. The method uses a convex linear combination of weighted similarity measures in its objective function.

Furthermore, field emissivity measurements of leaves show that there is useful spectral information that may be detectable by passive remote sensing in the thermal infrared (da Luz and Crowley, 2007). A number of organic materials and compounds present in leaves display characteristic TIR spectral features, although the appearance of such features is quite variable owing to interspecific differences in cuticle composition and structure. Remotely discerning the subtle emissivity features of leaves in their natural canopy geometries continues to present major technical challenges. In order to minimize spectral contrast losses due to canopy voids and multiple scattering, sensors having both a high signal-to-noise ratio and a field of view on the scale of individual leaves will be required. Atmospheric compensation methods and spectral analysis algorithms also will require refinement to permit the extraction of plant emissivity features. As technical capabilities improve, understanding the TIR spectral contributions of leaves will become increasingly important, and ultimately, may enable new types of remote sensing observations over vegetation canopies (da Luz and Crowley, 2007).

3. Weed detection for site specific spraying

Weed detection for site specific weed management is perhaps the most common application of machine vision related to site specific crop management. There are two aspects when weeds need to be automatically detected: (a) detection of weeds presence in the field while discriminating them from the crop itself; and (b) identification of the type of weed among all the detected weeds in order to fit the appropriate chemical for spraying. The first task is simpler since it has to distinguish between two classes, while the second task is more complicated since there are several different classes of weeds.

Detection of crop plants is the complementary task of detecting the weeds. Sometimes, this makes the task easier since the crop plants are usually more uniform than the weeds and have a more known geometrical structure. This approach is employed with selective herbicide application (Lee et al., 1999) and mechanical weeding systems which are based on the principle of continuously performing the weeding function while intelligently avoiding the crop plants (van der Weide et al., 2008; Tillett et al., 2008). Some of them use simple crop detection systems based on light interception (van der Weide et al., 2008) and others identify crop plants on the basis of a combination of color and shape parameters with classification algorithms, e.g., two-dimensional wavelets algorithms (Tillett et al., 2008).). In a slightly different approach, the generation of plants map can be performed during seeding or transplanting by recording their position while seeding or transplanting in the field. In this case, high accuracy and real time GPS systems have to be used (Ehsani et al., 2004; Sun et al., 2009). An accuracy of 2–3 cm in the mapped plant position has been reported, which makes this approach potentially applicable for selective herbicides spraying. The most significant error source in this approach was associated with the sensor that detected the seed or plant at the position where its location was recorded using the RTK GPS.

Nevertheless, the most commonly investigated task is detection of the weeds in the acquired images as well as identification of the weed species. Weed species identification is performed either by explicitly extracting the geometric shape of the weeds or by statistical pattern recognition methods. Some of the reported methods use also the structure of the rows as an additional support indication when assigning the detected objects to a class (crop plant or weed) (Shrestha et al., 2004). When spatial information about the rows is not included in the analysis, color and geometric features are used for discriminating weeds and plants. Color ratios are mainly used to extract the green material from the soil background and to discriminate between crop plants and weeds when there is a difference in their color (Bossua et al., 2008; Nieuwenhuizen et al., 2007; Marchant et al., 2004). The robustness of using color ratios for crop plant and weed discrimination is limited and depends on the local conditions.

Spectral leaf reflectance is used in several studies, to discriminate between crops and weeds. In controlled conditions in the laboratory, it has been shown that it is possible to discriminate with high accuracy between crop and weeds, as well as between weed species, using the spectral reflectance of the leaves (Borregaard et al., 2000). In field conditions though, the variability in spectral reflectance decreases the detection accuracy and, practically, only distinction between weed infected areas and weed free areas can be reliably performed (Goel et al., 2002). While there is evidence that spectral properties can be used to discriminate between a certain set of crops and weeds, frequently different wavebands are selected for each crop/weed pair. Research is needed over multiple seasons to investigate the stability of multispectral classifiers for plant species recognition of field crops and weeds (Zwiggelaar, 1998).

Texture analysis using color co-occurrence matrices (CCM) is one of the common methods of statistical pattern recognition and has been successfully used for weed species classification in different plant maturity stages (Burks et al., 2002). The hue, saturation and intensity of color images are usually used for CCM calculation. Different classification schemes select the texture variables with the greatest discriminant capacity, and combine them in discriminant analysis and artificial neural networks, to classify weed species within and across maturity levels. The achieved accuracy of weed species detection reaches as high as 97% (Burks et al., 2002, 2005, 2000). Statistical pattern recognition can be also applied on binary images: after plant material is extracted from the soil. Using the difference in multi-spectral images at 660 and 800 nm, cotton can be segmented from weeds using local inhomogeneity of pixel values (Alchanatis et al., 2005) and 86% of the pixels were classified correctly.

Geometrical shape of the green elements in an image has been also extensively used for weed detection. Combination of size, shape and color enabled detection and mapping of volunteer potato in corn and sugar beet fields (Nieuwenhuizen et al., 2007; Van Evert et al., 2006), as well as distinguishing between corn plants and weeds (Shrestha and Steward, 2005). Weeds' and plants' shape has been described by elliptic Fourier (EF) analyses (Neto et al., 2006) active shape models (ASMs) (Persson and Åstrand, 2008), wavelets and Gabor filers (Bossua et al., 2008). Shape features, combined with classification schemes of k-NN and discriminant analysis resulted to detection accuracy ranging from 80 to 97%. The method that employed ASMs managed to overcome problems of weeds occluding the crop, while wavelet based methods were able to process images with perspective distortion.

Accurate weed detection and mapping is essential for site specific weed management, but there is a trade-off between increasing the sensitivity of the detection system vs. the possibility of, in doing so, misclassifying some crop plants as weeds and inadvertently removing them. Examination of different competition scenarios between crop and weeds showed that combining a detection system with a competition model presents a new opportunity to quantify the sensitivity of image classification in terms of yield (Grundy et al., 2005).

3.1. Row detection

Row detection in precision agriculture is mainly associated with autonomous navigation or as an aid for weed detection. The majority of the developed systems use color images, taken with a perspective angle. Since crop lines are usually straight, most of the image processing algorithms for row detection are based on Hough transform, which has the inherent characteristic of detecting straight lines (Van Evert et al., 2006; Åstrand and Baerveldt, 2005; Gee et al., 2008; Bakker et al., 2008). Unlike the majority of reported algorithms, methods that do not rely upon the segmentation of plant material from the background are also reported. Rather, the periodic amplitude variation due to parallel crop rows is exploited. Given the geometry of the camera arrangement and the crop row spacing, a filter is derived which allows the crop rows to be extracted whilst attenuating the effects of partial shadowing and spurious features such as weeds (Hague and Tillett, 2001). In another work, row detection was performed by segmentation using color (Slaughter et al., 1999), K-means clustering algorithm, row detection by a moment algorithm, and guidance line selection by a cost function. Auxiliary information, such as the known crop row spacing, can be used to aid in the development of the guidance directrix (Han et al., 2004).

Row detection is broadly applied in the initial stages of crop growth, where the crop plants form a continuous line and row detection relies on the continuousness of the green objects. Nevertheless, systems that detect the seed rows have been also developed, to assist guidance of seeding machines (Leemans and Destain, 2007) as well as systems using laser ranging technology to detect swath edges for combine guidance (Coen et al., 2008).

Machine vision and laser radar (Lidar—Light detection and ranging) were individually used for guidance in orange grooves (Subramanian et al., 2006; Subramanian et al., 2005). Lidar-based guidance was found to be a better guidance sensor for straight and curved paths at speeds of up to 3.1 m/s. However, additional testing is needed to improve the performance. It was proposed that a control scheme, which used both machine vision and laser radar, may provide a more robust guidance, as well as provide obstacle detection capability. Obstacle detection was reported also using a stereo camera, having good performance when the obstacle was in the vicinity of the vehicle (Wei et al., 2005).

4. Crop water status using thermography

Thermography can be used to measure canopy temperature. Similarly to visible (RGB) or NIR images, thermal images contain spatial information about the imaged objects. On the other hand, they have two main basic differences: First, thermal infrared (TIR) images contain information about energy emitted as electromagnetic waves from the bodies surface, while RGB and NIR images contain information about electromagnetic energy reflected from the bodies surface. Second, the spectral range of the thermal infrared from 3 to 12 μm, while RGB and NIR images are in the range from 0.35 to 1.0 μm. RGB images are related to pigment absorption (chemical composition), NIR images are related to scattering (geometrical cell structure), and TIR images are related to the object's thermodynamic properties and emissivity, and surrounding conditions. Therefore, each image type has a different thematic content which makes them complementary.

The main sensing tasks in precision agriculture where thermal imaging plays a major role are mapping of crop water status, detection and mapping of crop diseases and detection of fruits in tree canopies. The temperature of the canopy has long been recognized as a measure of plant water status (e.g., Tanner, 1963). Recent developments in thermal imaging have opened opportunities for mapping of crop stresses, and mainly crop water stress using its temperature (Moeller et al., 2007). Much of the early work on thermography and water status estimation was based on handheld thermometers, which measure a temperature average over a single target area. Soil, trunk or dead tissue might be included in the sample area, potentially leading to considerable errors in estimated canopy temperature, particularly in sparse vegetation (Moran et al., 1994). Recent technological advances in thermal imagery offer the potential to acquire spatial information on surface temperature in high resolution.

Canopy temperature alone, cannot be an absolute indicator of water stress since it is affected by the meteorological conditions at the time of measurement. An index that normalizes these conditions was suggested, the 'Crop Water Stress Index', CWSI (Idso et al., 1981). CWSI is based on the difference between canopy temperature, as measured by infrared thermometry (IRT), and that of a 'non water-stressed baseline' referring to the temperature of a well watered crop.

The use of normalized CWSI using natural wet and dry reference surfaces was proposed by Clawson et al. (1989). This approach was used by Leinonen and Jones (2004) where they used plants as natural wet and dry reference surfaces. However, these natural surfaces might not necessarily be uniform and difficulties are likely to arise with regard to their reproducibility. Meron et al. (2003) addressed these problems by using an artificial wet reference surface (AWRS) for estimating the temperature of a well watered crop. The suc-

Table 1
Specifications of digital communication devices.

	ZigBee IEEE802.15.4	Bluetooth IEEE802.15.1	Wireless LAN IEEE802.11b/g/n
Frequency	2.4 GHz/915 MHz	2.4 GHz	2.4 GHz
Baud rate	250 kbps	721 kbps/2.1 Mbps	11/54/300 Mbps
Power consumption	40 mW	100–400 mW	0.5–6 W
Communication range	100–300 m	10–100 m	100 m–30 km
Energy efficiency	6 Mbps/W	7–21 Mbps/W	22–50 Mbps/W

cessful use of these artificial references on a sub-plot scale has also been reported by Cohen et al. (2005) and Alchanatis et al. (2010), who used thermal imagery for evaluating and mapping leaf water potential of cotton under various irrigation regimes.

Mapping the water status of larger areas by means of low altitude (50 m) airborne thermal imaging has been reported (Meron et al., 2010). Water status maps of cotton and peanut fields were created and validated. Canopy temperature was statistically extracted using histogram based analysis. Pixel by pixel processing was not possible due to the high degree of blurring, but the statistical analysis extracted only pixels that represented canopy temperature.

Due to their complementary nature, combination of visible RGB, NIR and TIR images can provide additional information. Thermal, in conjunction with visible and NIR images enable exclusion of non-leaf material in the estimate of canopy temperature and the possibility of selecting specific parts of the canopy for water stress estimation (Moeller et al., 2007; Leinonen and Jones, 2004; Alchanatis et al., 2006). Spatial patterns are created based on one of the images (e.g., color processing of the RGB image) and then superimposed on the other (e.g., mask on the thermal image). This allows isolating leaves that are exposed to uniform environmental conditions and enables better interpretation of their temperature according to known prevailing environmental conditions.

Combination of thermal with RGB data can be also used without directly associating spatial patterns from one image to another. Visible light imaging can be used to calculate changes in the surface structure and reflectance. Grey-level concurrence matrix (GLCM) texture features can quantify changes in the sample surface structure while RGB color ratios can detect changes in its reflectance. Combining those features with thermal images, Ondimu and Murase (2008) found a correlation between the water status of Sunagoke moss samples and their CWSI, GLCM texture and RGB color ratios. Although the reported study was performed only with Sunagoke moss, this method could be extended to both biotic and abiotic stress detection in other plants.

5. Sensor network for agriculture and field monitoring

Environmental data are very important in agriculture, since crop yields depend on environmental conditions, and the response of plant growth to changing environmental conditions is extremely complicated. In fact, the relationship is much more complicated than the ways it has been understood so far because the complexity is caused by chaos (Hirafuji and Kubota, 1994), and generally speaking, enormous amounts time-series data are required to predict/control chaotic systems.

Recently, high-throughput sequencing technology has enabled the determination of entire plant genomes in a short time (Shendure and Ji, 2008). However, phenotypic data of these varieties is still scarce because there have been no automatic tools to measure both the environmental and phenotypic data simultaneously. For example, Buckler et al. (2009) collected a huge set of phenotypic data manually to examine variations in flowering time of 5000 recombinant inbred lines (maize Nested Association Mapping population, NAM) in eight environments, using a total of one million plants, since flowering time is a complex trait that controls adaptation of plants to their local environment.

Thus, we need to collect enormous amounts of data in the field. On the other hand, it is reasonable to assume that huge amounts of weather data must already be available if all the databases in the world are integrated. Laurenson et al. (2001, 2002) actually combined almost all weather databases by developing data-grid middleware, MetBroker. MetBroker provides a standardized software interface for programmers to develop agricultural applications quickly. As a result, weather data from about 23,000 sites are integrated and can be viewed on integrated maps. While 23,000 seems like a large number, in fact only one weather station exists per 21,000 km^2 on average. There are few weather stations in the interior of countries. To make matters worse, important data such as solar radiation, soil moisture and CO_2 concentration, which affect plant growth, are not collected.

Farmers and researchers must obtain data at their sites by themselves, but conventional weather stations are too expensive and too large. So far, data loggers have been employed for such purposes, but users must visit these stations frequently simply to collect the data. To solve these problems, sensor networks are desirable.

5.1. What is wireless sensor network?

A wireless sensor network consists of distributed sensor nodes which contain sensors and a wireless communication device. Nowadays, as commercial products of sensor nodes, MOTE,[6] Field Server,[7] SUN SPOT[8] and many kinds of products using ZigBee (IEEE802.15.4)[9] are already available. The actual size of these sensor nodes, equipped with a waterproof case for outdoor deployment, is not so small. The diameters are 10–20 cm, or sometimes much larger, with poles to fix them on the ground, solar panels, rechargeable batteries and external sensors. In the future, a sensor node will be a single chip and its size might be as small as a dust particle (Kahn et al., 1999). Although the size is not important for use on farms, it would truly be a great advantage if the cost of sensor nodes fell, as in the case of pocket calculators.

Almost all these sensor nodes use 2.4 GHz radio waves, which are well absorbed by water molecules, as microwave ovens use this frequency. A sensor node that uses a wireless device is legally available after its manufacture obtains a certification from the country's communications authority: for example, the FCC in the United States. We can find the certification logo "FCC" on the back of wireless communication appliances. The communication range of Wi-Fi can be enlarged by using high-gain directional antennas under the certification. So far most commercial sensor nodes for factories employ ZigBee. However, Wi-Fi has the highest efficiency and the longest communication range (Table 1). Currently, Wi-Fi is best for practical sensor networks in open fields. Yet we have a difficult problem that the communication range is not sufficient for the size of most farms. Microwave radio cannot permeate through

[6] http://www.xbow.com/.
[7] http://www.elab-experience.com/.
[8] http://www.tauzero.com/Rob_Tow/Sun-SPOTS-Sensor-Networks.html.
[9] http://www.zigbee.org/.

obstacles such as mountains, forests, buildings and metallic walls. A line of sight is indispensable to establish connection.

A solution to this problem is to relay information. Long distances can be connected by multi-hop relay, and a detour by the relay network can avoid large obstacles. This method has other advantages: energy saving and robustness of sensor networks. The electric field intensity of the radio wave, E, is attenuated to the distance of the transmitter and receiver, r, as:

$$E(r) \propto \frac{1}{r^2} \tag{1}$$

If the distance, r, becomes half, then E increases by a factor of 4; hence, we can decrease the power of the transmitter up to 1/4 to maintain the same electric field intensity. Then the total power consumption can be decreased to a half. In fact, the total power consumption of electric devices such as receiver, sensors and camera cannot be neglected. In any case, multi-hop relay can connect sensor nodes in a wide area effectively, and the wireless sensor network can measure spatially an area where the sensor nodes are deployed (Fig. 1). Mesh-networking can keep connections among sensor nodes even if some sensor nodes are broken. Simultaneously, they can provide the service of Wi-Fi hotspots, where farmers, residents and visitors can connect to the Internet. Mesh-network protocol is supported by ZigBee and some low-cost Wi-Fi routers such as Meraki[10] and RMR.[11] While the Wi-Fi mesh network standard, IEEE802.11s, is still in the drafting process, OLPC (One Laptop per Child),[12] previously known as the "$100 Laptop", also employs a Wi-Fi mesh network, which is very useful for constructing *ad hoc* wireless network infrastructure in developing countries. The situation of network infrastructure that OLPC is assuming is exactly the same as that of the wireless sensor network in agriculture.

5.2. Sensor networks for agriculture

Precision agriculture demands intensive field data acquisition. Frequent data acquisition and interpretation can be the key to understanding productivity variability. Wireless sensor networks are a new technology that can provide processed real-time field data from sensors physically distributed in the field (Camillia et al., 2007). Typical applications of sensor networks in agriculture are:

– Management of farming
– Precision agriculture
– Optimization of plant growth
– Surveillance in farms
– Advertisement for consumers
– Education and training for better farming
– Research

The applications of sensor networks using ZigBee are numerous (Baggio, 2005; Hebel, 2007; Ruiz-Garcia et al., 2009; López Riquelmea et al., 2009). Sensor networks using ZigBee are connected to the Internet through a gateway node, which functions as a media converter from ZigBee to the Internet. However, network infrastructure in rural areas is poor in general. The emergence of 3G (International Mobile Telecommunications-2000) and WiMAX in rural areas promises to increase access to alternative media except for the problem of cost. Wireless LAN (Wi-Fi) is useful as a long-range wireless communication technology for sensor networks. Simultaneously, it can be a wireless network infrastructure for residents and farmers working on farms to have ubiquitous Internet services (Hirafuji, 2000).

Sensor nodes for agriculture must be durable and rugged to protect the electric devices in the cases. This is their most characteristic feature in comparison to sensor networks designed for industrial use. Environmental conditions to deploy sensor networks for agriculture are very diverse. In a sense, farms are extreme environmental fields, with very wide ranges of ambient air temperature (between −40 and 50 °C) and relative humidity (0–100%). Moreover, there are interferences caused by agricultural chemicals and organisms such as livestock, insects, plants and microorganisms. For example, sensor nodes are exposed to the menace of being trampled by cows at ranches (see sensor network Web sites[13,14]). Especially for long-term real-time observation under such extreme environments, there exist a lot of site-specific problems to be solved each time (Hirafuji et al., 2008a,b). Data frequently goes missing due to failures caused by various reasons (Kotamäki et al., 2009). For example, some electric devices such as electrolyte capacitors and lead-acid batteries cannot work normally under extremely low temperature, and CPUs are hung up under higher temperature, like PCs, which are often hung up even at room temperature. Cases and cables of sensor nodes are gradually eroded by thermal expansion caused by changing temperature, strong solar radiation, chemicals, heavy rainfall and strong wind; finally, condensation on printed circuit boards corrodes the wires of electric components and printed circuits.

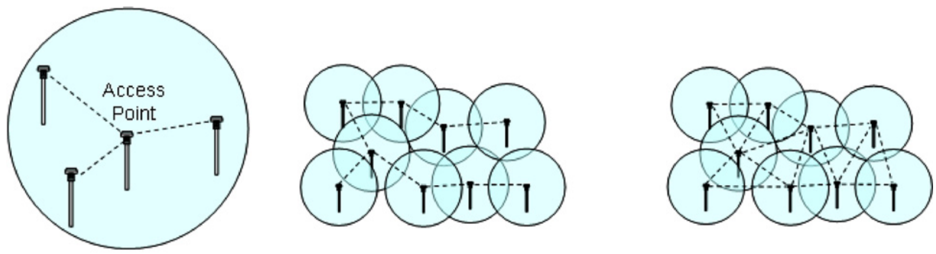
Sensors are affected by environmental conditions in the open field: for example, temperature sensors to measure ambient air temperature are affected by solar radiation. So the temperature sensor must be isolated carefully from such artifacts. Unfortunately, most sensor nodes are packed in simple plastic cases, since this kind of equipment was not originally designed as meteorological data acquisition systems. The worst measurement errors by some commercial sensor devices, which are sold at stores for general purposes, were 3–10 °C for solar radiation and radiative cooling. This range of error is not acceptable in agricultural applications such as plant growth models, since accumulated temperature is frequently used for predictions of flowering and yield of crops (Hirafuji, 2009).

Hirafuji and Fukatsu (2002) developed a multifunctional sensor node that can collect many kinds of data for agricultural applications. The Field Server functions as a web server, a Wi-Fi access point, IP camera (network cameras), LED lighting, and a sensor node on farms (Fig. 2). The Field Servers have been deployed at many sites globally for agricultural researches (Hirafuji et al., 2007). A localized Field Sever was developed in Thailand, and several hundreds of Thai Field Servers were deployed in Thailand for research and education (Paiboonrat, 2006). Wan et al. (2008) deployed Field Servers that were constructed by their group in order to secure food production at chicken farms. Several Field Servers were deployed in Himalaya to monitor the melting of Imja glacial lake located beside Mt. Everest (Fukui et al., 2008; Hirafuji et al., 2008a,b; Pun et al., 2008). Practically, Field Servers can be used as a method of public relations for consumers[15,16] and residents.[17]

5.3. Data collection and applications

Sensor network applications for agriculture are being developed rapidly, and the results have been reported at international con-

[10] http://meraki.com/.
[11] http://www.thinktube.com/en/.
[12] http://laptop.org/.
[13] http://fsds.dc.affrc.go.jp/data3/Kouzu/.
[14] http://research.ict.csiro.au/.
[15] http://www.ucc.co.jp/company/livecamera/.
[16] http://www.quark.bio.mie-u.ac.jp/olive/en/index_en.html.
[17] http://www.iwatou.net/fs/.



(a) Access Point and Clients (b) WDS (Wireless Distribution System) (c) Mesh network

Fig. 1. Types of wireless networks. Circles indicate Wi-Fi hotspots, where users can access the Internet by Wi-Fi. ZigBee networks cannot serve as Wi-Fi hotspots.

(a) Field Servers at a paddy field in Japan (b) Mote and Field Server in India

Fig. 2. Deployments of sensor networks in farms.

ferences such as WCCA,[18] AFITA,[19] EFITA,[20] INFITA[21] and APAN.[22] Discussions towards data integration and standardization are being held in several groups such as the Sensor Web Enablement Working group in OGC (Open Geospatial Consortium) and the GEOSS Sensor Web Workshop in GEO (Group on Earth Observation). Note that the terminology "sensor web" was first used by NASA to describe their wireless sensor network for surveillance of Mars (Delin and Jackson, 2000). Their sensor web was not a web server. The meaning of the term "sensor web" has been extended to WWW services including sensor networks or Web-based sensor networks (Quan et al., 2009). So far sensor data have been recorded as binary data files, text files (CSV) or records of DBMS. Some of such data files have been lost. The rests are archived as so-called "legacy data", since applications cannot read data files without metadata (information to describe the data files). Recently XML has emerged as a common machine-readable file format, by which an application can read another application's data file (XML) automatically using its metadata file (XML).

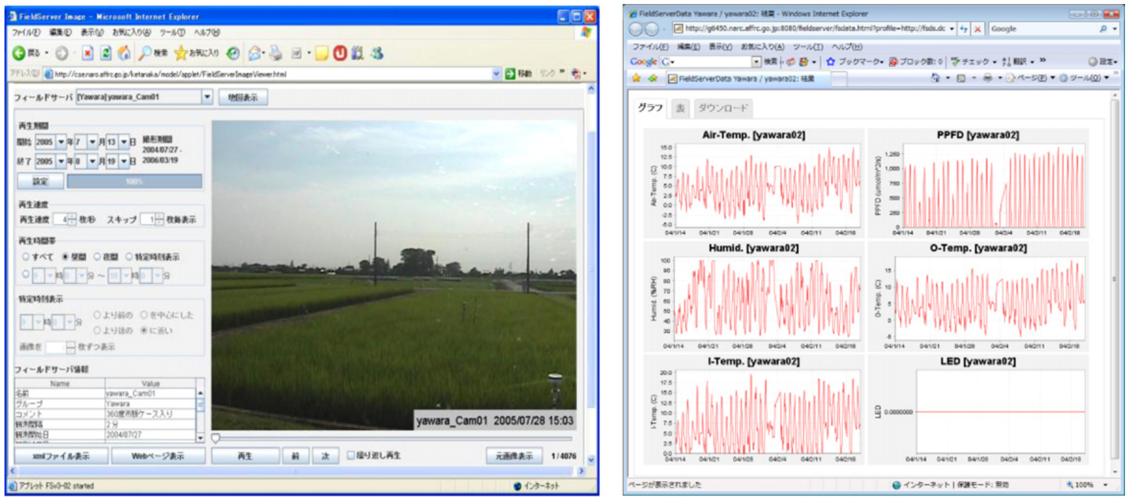
Hoshi et al. (2003) proposed an information exchange standard format on XML for plant production (BIX-pp). Using BIX-pp, they developed an application for sensor networks constituted by the Field Servers. The application can record many kinds of data such as plant growth, farm work, use of agricultural chemicals, amount of products, etc. (Hoshi et al., 2007). Honda et al. (2009) integrated sensor data and Web GIS using SOS (Sensor Observation Service), which is a standard web service interface (i.e., API) for managing deployed sensors and retrieving sensor data.

Conventional sensor nodes automatically send data: it is "push-type" sensor node. On the other hand, Web-based sensor nodes (e.g. Field Servers) wait to be accessed by users or other computer programs such as agents and applications: it is "pull-type" sensor node (Hirafuji et al., 2009). Users can control the pull-type sensor nodes easily, simply by using a Web browser such as Internet Explorer (Fukatsu and Hirafuji, 2005). Instead of a user's manipulation, the agent accesses Web-based sensor nodes to collect sensor data, and then stores the data converted into XML files and HTML files for a Web server, which works as a user interface to share the data (Fig. 3). An architecture based on an agent and Web-based sensor network (Fukatsu et al., 2006) constitute the concept of the Sensor Web. For example, programmers can develop applications in a short time by a mashup of the Web-based sensor networks and other Web services (e.g. Google Maps). Tanaka and Hirafuji (2009) demonstrated complex applications developed by a mashup of Google Earth, agricultural models, weather databases and sensor networks. The Web-based sensor networks are advantageous in terms of the scalability of the sensor networks; the agent can collect data from an enormous number of sensor nodes sequentially. This manner is similar to a Web crawler which collects indexing data over all Web servers automatically. If an enormous number of push-type sensor nodes send data into a data storage server at once, their attempts at access would damage the storage server, for instance resulting in DDoS (Distributed Denial of Service).

5.4. Advanced sensing for agricultural sensor networks

Sensor networks are able to collect high-resolution images at farms in real time (Fig. 4). Such image sensors are thought to be a kind of universal sensor: they can be used for remote sensing to monitor plant growth, real-time surveillance against the deceptive labeling of production centers and bio/agro-terrorism (Hirafuji et al., 2004). Plant growth rate can be measured by images. For example, Iwabuchi and Hirafuji (2002) found that plant seedlings rotate by circumnutation at night, and the growth rate of each seedling can be estimated by the maximum speed of rotation. Speed of rotation can be easily measured from time-lapse images using optical flow technique (Fig. 5). Tanaka et al. (2008) developed a Web application to detect unusual changes in images, since sensor networks

[18] http://www.wcca2009.org/.
[19] http://afita2010.ipb.ac.id/index.php/afita2010/afita2010.
[20] http://www.efita.net/.
[21] http://www.infita.org/.
[22] http://www.apan.net/.



(a) Collected image data (b) Collected sensor data

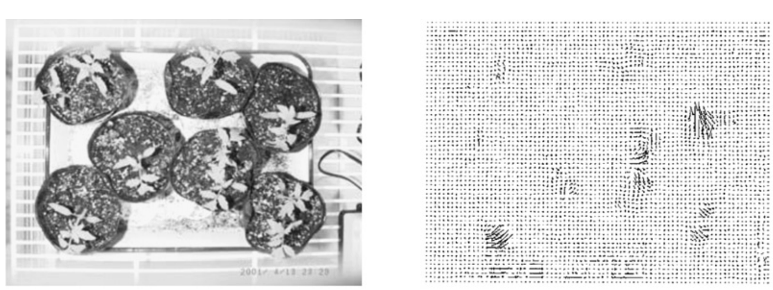
Fig. 3. Examples of collected data from sensor networks.

Fig. 4. A sample image of a potato farm. The right picture is the rectangular part in the left picture. This picture was taken by a digital single reflex camera equipped in a sensor node, deployed at Namche Bazaar, Nepal. http://fsds.dc.affrc.go.jp/data4/Himalayan/.

collect too many images for users to find important changes such as unlawful dumping on farms. Using this application, Asai et al. (2008) found that crickets (*Teleogyllus emma*) were the primary seed predators of wild oat and Italian ryegrass, which are problematic weeds in small-grain cereal fields in Japan. Cropping systems involving a summer no-till period reduce the density of the subsequent generation of weeds in comparison with tilled rotation systems. Extending the duration of the no-till period suppresses weed seedling recruitment. Unusual images among the enormous number of images collected by sensor networks revealed that this suppression was caused by crickets (Fig. 6).

Hashimoto et al. (2007) developed an integrated field monitoring system for sustainable and high-quality production of agricultural products combining sensor networks and advanced sensing technologies, including X-ray fluorescent (XRF) and mid-infrared (MIR) spectroscopic analysis of leaves to evaluate nutrimental elements of the plant vigor.

Oki et al. (2009) developed an integrated agricultural monitoring system based on the use of high-spatial-resolution remote sensing imagery and data on sensor networks in a cabbage farm. It can produce cabbage coverage maps that provide information on cabbage growth that could be used for agricultural land management, particularly with regard to the application of fertilizer and forecasting of crop production. Hirafuji et al. (2008a) developed an insect counter for sensor networks. Although the count data may contain noise caused by raindrops on windy condition, fake



(a) Seedlings of tomato plants in pots (b) Vectors of motion speed of the seedlings

Fig. 5. Motion speed measured by optical flow of time-lapse images.

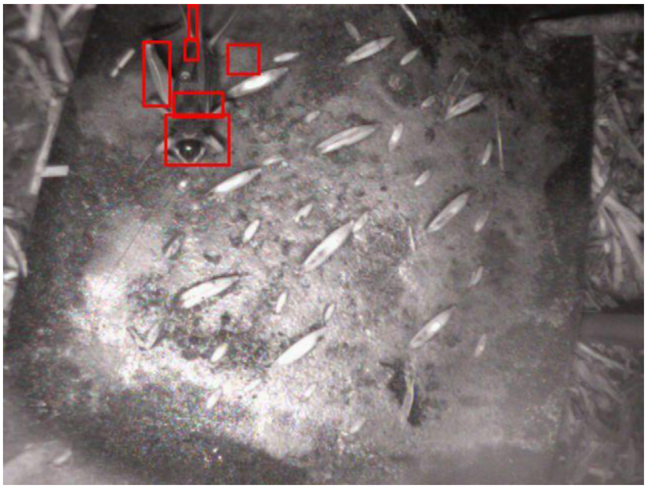


Fig. 6. A cricket (*Teleogyllus emma*) captured by infrared camera. Crickets appear every night to eat the seeds arranged under the IR camera.

counts can be eliminated by using the images. Thus, sensor networks equipped with multiple sensors can improve the reliability of sensor data with assistance of sensor fusion technology.

5.5. Discussion

Agro-ecosystems and environments in farms are not uniform, so sensor networks are indispensible for collecting spatial time-series data and time-lapse images in real-time. Sensor nodes for agriculture should equip a lot of sensors and cameras to measure both environments and crops simultaneously. Such sensor networks can be a key technology for precision agriculture, water-saving cultivation and sustainable agriculture. In the future, sensor networks will be a method of *in situ* phenotyping by sensing more biological data such as microscopic images, proteins and sugar chains on site; the synergistic effect with recent high-throughput sequencers will make breakthroughs in biology and agricultural sciences.

As for the shortage of network infrastructure in rural areas, choosing the optimal combination of Wi-Fi, ZigBee, 3G and WiMAX can be a solution. Sensor networks have been deployed even in developing countries and extreme situations. However, it is still a difficult problem to cut the cost of sensor networks. In principle, the following points are required for widespread deployment of sensor networks in agriculture and field monitoring:

– Low cost
– Easy to use
– Durable and rugged
– Long-range communication
– Scalability to a high number of sensor nodes

All of these objectives have been accomplished except for “low cost”. Mass production may realize low-cost sensor networks since the price of commercial products generally depends on the number of products sold. The price of sensor nodes can be sufficiently decreased only by producing 1000 units. If orders are million or billion units, then the cost can be 1/10–1/100. For example, currently the cost of a hand-made Field Server is about US$1000. If one million Field Servers were produced by automation, the cost could be less than US$100. Such low-cost sensor nodes can be deployed in high density, and long-range communication can be realized by relaying among the sensor nodes. Moreover, the greater the number of sensor nodes, the more robust the sensor network.

Let us assume that the MTBF (Mean Time Between Failure) of a sensor node is 1 year, and 12 sensor nodes are deployed. Then one failure per a month is observed on average, but the sensor network can keep working continually for several years without maintenance simply by relying on the sensor nodes that are still active. On the contrary, if only one sensor node is deployed in the site, data is missing after its failure and maintenance is needed every year. Mass production is still difficult in this initial stage of introducing sensor networks in agriculture. Investigation for durable sensor nodes with longer MTBF may realize the “low cost” objective without mass production. Moreover, mass production can cut more costs after this initial stage, and then spatial time-series data in fields will be more easily available.

6. Canopy volume/crop biomass detection

Canopy volume of tree and other specialty crops is an important factor for precise fertilizer application, irrigation, chemical applications, as well as health assessment (Smart et al., 1990; Haselgrove et al., 2000; Wood et al., 2003). It relates to crop yield for tree crops. Smart et al. (1990) described the relationship between canopy management and yield for grape. Haselgrove et al. (2000) discussed light exposure and phenolic compounds of berries in different canopy conditions. Wood et al. (2003) investigated the relationship between pistachio nut fruit ripening date late season canopy retention.

There have been several attempts for canopy volume assessment, utilizing different methods such as ultrasonic, laser scanning, aerial sensing, and light penetration measurement of the canopy. These different methods are described below. As an earlier work, Turrell et al. (1969) studied the changes in feature data of citrus trees over a period of time. They discussed establishing growth equations for different variables for the citrus varieties using aboveground tree parameters including tree height, branch size and number, leaf surface area, number of leaves, and many others (trunk diameter, fruit yield, fruit size, fruit diameter, fruit weight, woody frame, branch number, root density, and yield). Results showed that citrus trees and tree parts followed growth curves similar to non-woody plants. A significant amount of the physico-chemical processes that underlie tree growth were found to be linear semi-log or log-log functions. In the 1970s, Albrigo et al. (1975) evaluated various tree measurements (canopy fruit bearing densities, tree height, canopy skirt height, canopy max diameter in horizontal plane, and vertical height to max diameter) to determine reliable yield and reported that the R^2 between canopy volume and fruit weight ranged from 0.24 to 0.85 using multiple stepwise regression and correlation to yield, and that no other combination of the variables predicted accurate yields. This information was all measured manually.

6.1. Laser scanning

Since 1970s, laser ranging has been used in many areas, however it was the late 1980s when the laser technology was used for forest biomass detection and crop production. Nelson et al. (1988) implemented an airborne pulsed laser system to assess forest biomass and timber volume. The same technique could be applied to specialty tree crops for canopy volume assessment. They used a frequency-doubled Nd:YAG laser at 0.532 μm to acquire the profiling data. They reported that airborne laser profiling data was used to successfully estimate tree volume within 2.6% of the true mean. They also reported site specific variability of tree volume and biomass. In the 1990s, Ritchie et al. (1993) utilized a laser altimeter to quantify vegetation properties. Results showed a variation in the canopy heights between 2 and 6 m and the maximum heights measured correlated well with the data obtained from other methods. This study showed a potentially similar application to specialty tree crop production. A helicopter-borne laser system was also implemented to measure tree heights and stand volume (Nilsson, 1996). They recommended the combination of airborne Lidar and satellite imagery could be very useful for describing biodiversity and monitoring its changes.

With the advancement of technologies, a newly developed sensing system was applied to specialty crops. Wei and Salyani (2004) applied a laser scanning system (AccuRange AR4000–LIR, Acuity Research Inc., Menlo Park, Cal.) to measure citrus tree height, width, and canopy volume. They tested the system to determine its resolution and accuracy and reported that the system showed good repeatability with measurement errors less than 5%. This type of canopy characteristics study is important in the development of tree specific or site specific management practices. Further, Wei and Salyani (2005) implemented a laser scanning system to measure the foliage density of a citrus canopy. When compared with manually collected data, the results showed an overall correlation of $R^2 = 0.96$ with an RMSE = 6.1%. The laser measurements showed a good repeatability with an average coefficient of variation (CV) of less than 3%. More recently, Ehlert et al. (2008) also utilized a laser system and implemented a laser rangefinder technology to estimate site-specific crop parameters such as plant height, coverage and biomass density which could be a major factor in optimizing crop harvesting methods. The results showed a correlation of 0.93–0.99 for oilseed rape, winter rye and winter wheat between the crop biomass density and the mean height of the laser reflection point.

6.2. Ultrasonic sensing

Another technique used to measure crop canopy is ultrasonic sensing. Ultrasonic sensors were used in crop production starting the late 1980s. Giles et al. (1988) used commercial ultrasonic range transducers to measure tree canopy volume. The system was mounted and tested with an air blast sprayer and the results showed an error rate of less than 2% on calibration targets and an average error of 10% for apple and peach orchards applications. They reported that the results could be used as a means of sprayer control in the future. Then, Giles et al. (1989) investigated spray volume savings using an ultrasonic measurement which ranged between 28 and 52%, and varied greatly depending on target crop structure. Moltó et al. (2001) also investigated the possibility of saving the chemicals by measuring the distance between the sprayer and tree canopy using ultrasonic sensors and reported savings of spraying products up to 37%. Other similar studies also reported chemical saving in spraying operations. Solanelles et al. (2006) tested a prototype sprayer with an electronic control system containing ultrasonic sensors in olive, pear and apple orchards, and reported 28–70% spray product savings when comparing spray deposits to a conventional application. Gil et al. (2007) also reported an average of 58% less liquid applied using ultrasonic sensors when comparing a uniform application rate with variable rate of a sprayer based on vineyard structure variations.

Other groups of researchers conducted studies in different aspects of ultrasonic sensor application. Tumbo et al. (2002) reported comparison between a laser scanner and ultrasonic transducers in measuring canopy volume of citrus trees. When compared with manual measurements, ultrasonic measurements yielded an R^2 of 0.90 with an RMSE of 1.7 m^3, while laser measurements yielded an R^2 of 0.95 with an RMSE of 1.9 m^3. The laser sensor system performed slightly better since it had a higher resolution. Zaman and Salyani (2004) investigated the effect of travel speed on ultrasonic measurement of citrus tree canopy by a Durand–Wayland ultrasonic system. For dense foliage, the travel speed did not affect much to canopy measurement, yielding standard errors of 1.0–1.1% compared to manual measurements, while light foliage measurements were affected more by the travel speed with 1.5–3.0% standard error in canopy volume measurement. They reported that the opening in the canopy and light density of foliage might reduce the ultrasonic signal to result in poor performance in light foliage measurements. However, the ground speed did not produce any significant effect on canopy volume measurements. Schumann and Zaman (2005) developed a real-time software system to map citrus tree canopy volume and height using ultrasonic sensors and a DGPS receiver. The system continuously monitored the ultrasonic sensors and the DGPS receiver, and measured the tree size and canopy volume. They reported high accuracies between manual and the automated measurements with R^2 values of 0.94 for tree height and canopy volume. Balsari et al. (2002) developed a prototype sprayer which could measure target size and density of apple trees using ultrasonic sensors and found that travel speed did not significantly affect the vegetation measurement using the sensor, and suggested that an average of at least 10 measurements in every meter of travel distance would be needed for proper adjustment of the sprayer.

6.3. Light penetration of the canopy

Another method used to determine the foliage density of trees was the light penetration of the canopy (Jahn, 1979). Past studies showed that the light penetration was a non linear measurement of the leaf density. Jahn (1979) used the radiation measurement as a means of estimating canopy density. The trees under study were defoliated at different levels to obtain their radiation penetration. The tree size was used to determine the leaf area index (LAI) and the leaf area to canopy area ratios (LAC). Results showed that the penetration of photo synthetically active radiation (PAR) increased in a curvilinear fashion as defoliation increased and LAC decreased.

6.4. Other crop biomass sensing methods

Besides laser scanner and ultrasonic sensors, satellite imagery or synthetic aperture radar (SAR) satellites were also used for crop biomass sensing. Todd et al. (1998) estimated biomass of rangelands using spectral indices from the LANDSAT TM imageries. This method studied the use of green vegetation index (GVI), brightness index (BI), and wetness index (WI), the normalized difference vegetation index (NDVI) and the red waveband (RED) in the estimation of biomass content of ungrazed and grazed grasslands. The results showed the close correlation of the GVI, NDVI, WI and RED indices to the biomass from grazed sites, however found no significant relation in the data from ungrazed sites. Lu (2006) reviewed articles for remote sensing-based biomass estimation for forests sites and reported that the task would be challenging due to complex forest stand structure and environmental conditions. Lu pointed out that the following factors were important for successful measurement: accurate atmospheric calibration, selection of suitable vegetation index, integration of optical and radar data, integration of multi-source data, and reduction of the mixed pixel problem. Holmes et al. (2005) described the use of SAR satellites on estimating biomass and LAI, and reported strong relationships between the SAR backscatter and crop parameters (biomass and LAI).

6.4.1. Application of canopy measurements

One of the ultimate goals of estimating canopy volume is site-specific variable rate application of fertilizer and pesticides. Zaman et al. (2005) generated a prescription map for variable nitrogen application to citrus trees from the measurements of tree sizes by the ultrasonic system, and reported that 38–40% of granular fertilizers were saved when variable nitrogen applications were implemented on a single-tree basis. As described previously, other researchers also reported savings in chemical application based on canopy volume measurements (Giles et al., 1989; Moltó et al., 2001; Solanelles et al., 2006; Gil et al., 2007). Further, Zaman et al. (2006) mapped a citrus grove with an automated ultrasonic system and a sensor-based automatic yield monitoring system. They found that ultrasonically-sensed tree sizes were linearly correlated with fruit yield (R^2 = 0.80).

7. Soil nutrients and other soil characteristics

For soil nutrients and other characteristics, many different sensing methods have been studied and implemented including NIR and MIR spectroscopy, spectral library, electrodes, thermal imaging, Raman spectroscopy, fluorescence, and microwave. These methods are individually described below.

7.1. Visible (VIS)/NIR spectroscopy

Advances in spectroscopy have provided new methods to determine concentration of elements in chemistry. One of the most common methods is ultraviolet (UV), VIS and NIR reflectance spectroscopy. It has advantages in determining soil properties rapidly and non-destructively. A lot of research has been conducted on this topic at different locations around the world. The application of NIR reflectance spectroscopy (NIRS) to soil property sensing was initiated in the 1960s, made advances in the 1970s and 1980s, and bloomed in the 1990s. Starting in late 1990s and 2000s, real-time sensing systems were developed and some commercial systems became available for crop production.

One of the soil properties that were first investigated was soil organic matter (SOM) content since it is an important property when soil fertility is considered for crop production. Bowers and Hanks (1965) investigated the effect of organic matter on reflectance measurements and reported that reflectance decreased as moisture content increased, and that soil moisture determination might be possible by measuring reflectance. Other researchers investigated the infrared spectra of inorganic compounds (Nyquist and Kagel, 1971), identified wavelengths (0.624 and 0.564 μm) for predicting percent organic matter content (Kirshnan et al., 1980), studied the characterization of organic matter in particle-size fractions (Ristori et al., 1992), utilized an NIR soil sensor to predict soil moisture and organic matter content (Hummel et al., 2001), implemented radial basis function networks (RBFN) for soil organic matter detection (Fidêncio et al., 2002), and the effect of soil moisture and vegetation cover on the prediction of organic matter and clay content (Kooistra et al., 2003). Soil organic carbon (SOC) content is also an important constituent in SOM. Several different methods have been used for determining SOC, which include linear regression models (Ingleby and Crowe, 2000), the effect of particle size (Cozzolino and Moroǐn, 2006), NIR and fluorescence techniques (Rinnan and Rinnan, 2007), PLS regression (Vasques et al., 2008), and spectral indices (Bartholomeus et al., 2008). Along with these studies, soil mineral-N was also studied. Ehsani et al. (1999) investigated soil NIR reflectance to determine soil mineral-N content in 1100–2500 nm. PLS and principal component regression (PCR) were used to develop calibration models. They reported that the models were quite robust, however if some other interfering factors were not included in the model development, the calibration models failed, suggesting site-specific calibration would be necessary.

Another important soil property is moisture content. Since there are several very well known water absorption bands (for example, 960, 1410, 1460, and 1910 nm), NIR spectroscopy would be suitable to determine water content. Kano et al. (1985) designed and tested a soil moisture meter using NIR reflectance at 1800 and 1940 nm and reported that a standard error of ±1.9% moisture units. Dalal and Henry (1986) investigated simultaneous prediction of soil moisture, organic C, total N content of dry soils using NIR reflectance in 1100–2500 nm. Using multiple regression, they selected important wavelengths for the different soil properties. Slaughter et al. (2001) studied the feasibility of utilizing a global NIR calibration equation to determine soil moisture content and reported that NIR absorbance data was well correlated with soil moisture content when the calibration set contained the same soil type and particle size as the unknown samples, however the model did not work well when unknown samples had different soil particle size. Kaleita et al. (2005) reported an exponential model was suitable to estimate soil moisture from reflectance data. Mouazen et al. (2006) described the impact of soil water content on the accuracy of VIS and NIR spectroscopy on the estimation of other soil characteristics. The results showed a 95.6% correct classification of water content levels for the validation data sets using three water content classifiers on soil with limited texture and color variation.

As people became more concerned about the contamination from excessive agricultural chemicals, phosphorus (P) became one of the most concerning nutrient elements. Yoon et al. (1993) investigated an on-line phosphate sensing using optical measurement, ultraviolet photoluminescence and laser-Raman spectroscopy for P mining industry. They reported that approximately 20–30% error was produced for optical measurement, and significant data scatter was problematic due to small size of the incident light beam. Bogrekci et al. (2003) studied the wet and dry soil reflectance for determining P concentrations. Further, Bogrekci and Lee (2005a,b,c,d) conducted a series of research toward the development of a portable P sensing system, which include the feasibility of NIR to determine soil and grass P concentrations (Bogrekci and Lee, 2005a), the effects of soil particle size on the reflectance (Bogrekci and Lee, 2005b), spectral signatures of soils (Bogrekci and Lee, 2005c), examination of spectral characteristics of four common soil phosphates (Al, Fe, Ca, and Mg phosphates) in Florida (Bogrekci and Lee, 2005d), and the effect of soil moisture content on sensing P concentrations Bogrekci and Lee (2006a). Maleki et al. (2006) also measured reflectance of fresh soils in 300–1700 nm and developed P prediction models with R^2 values of 0.63–0.75. Further, Maleki et al. (2007) tested the previously developed portable VIS-NIR P sensor for variable rate application of elemental P, and reported that different averaging windows needed to be used to minimize the fluctuation of application rates since there was no variable rate (VR) equipment that could respond rapid fluctuations. Then, real-time application of phosphate (P_2O_5) was implemented during maize planting using an on-the-go visible and NIR soil sensor for extractable phosphorus in 305–1171 nm (Maleki et al., 2008). A comparison was made for crop yield and the number of plant leaves between VR and uniform rate (UR) plots, and they reported that no significant difference was found between the number of plant leaves in VR and UR plots. However, the yield was significantly higher in VR plots than in UR plots. Mouazen et al. (2007) compared on-line sensor measurement of different soil properties (P, C, pH, and moisture content) with those made under non-mobile laboratory conditions, and reported that similar results were obtained which suggests the possibility of real-time soil property sensing. Bogrekci and Lee (2007) compared the three different electromagnetic regions (UV, VIS, and NIR) to determine optimal region for detecting soil P, and reported that the NIR region yielded the best results based on PLS analysis results.

Additionally Raman spectroscopy was used for measuring soil P contents. Bogrekci and Lee (2005e) developed a portable Raman sensor for detecting P content in soil and vegetation using a 785 nm laser probe assembly and a detector array in 340–3460 cm^{-1}. They reported an R^2 of 0.98 and the lowest root mean square error

(RMSE) of 151 mg/kg for P predictions using PLS analysis. Further, Bogrekci and Lee (2006b) studied the effect of soil particle size on Raman spectra of soils and reported that soil particle size had an effect on Raman spectrum of soils and that the predictions using PLS showed higher coefficient of determinations when the same particle size of samples were measured than different particle size of samples were used.

Some researchers studied soil particle size along with NIRS application, such as investigation of the variation of diagnostic features with soil particle size and packing density (Arnold, 1991), prediction of soil texture (Zhang et al., 1992), and estimation of soil particle size by remote sensing (Salisbury and D'Aria, 1992).

Along with all the research, there were many groups of researchers who developed soil sensing systems. Shonk et al. (1991) developed a prototype soil organic matter sensor using red LEDs (660 nm) as a light source. They reported that the R^2 between actual and sensor-measured organic matter contents were 0.85–0.96 in a laboratory test, and that soils with organic matter content more than 6% would be difficult to estimate based on their test results. Sudduth and Hummel (1993a) developed a portable spectrophotometer to measure soil properties, then tested it in a laboratory and a field (Sudduth and Hummel, 1993b), and correlated NIR reflectance spectra with soil organic matter, CEC, and moisture content. They reported that in-furrow tests did not provide accurate estimates due to the movement of the sensor during wavelength scanning. Then, Sudduth and Hummel (1996) tested the previously developed NIR soil sensor with soil samples obtained various regions and reported that the calibrations became less accurate due to the extended geographic range of the samples. Shibusawa et al. (1999) developed a portable spectrophotometer for measuring underground soil reflectance in real-time in 400–1700 nm. They reported that R^2 values of 0.19 to 0.87 between reflectance spectra and different soil properties (moisture, pH, EC, SOM, NO_3-N). Then, Shibusawa et al. (2001) revised the soil spectrophotometer to collect soil reflectance data in a paddy field and predict soil moisture, SOM content, NO_3-N content, pH, and EC, and reported the R^2 values of 0.54–0.66 for the validation samples. Mouazen et al. (2005a) developed a portable NIR spectrophotometer in 306–1711 nm to measure soil moisture content during field operation. They reported a validation correlation of 0.978 between the actual and predicted moisture content. Further, Mouazen et al. (2005b) used the previously developed portable spectrophotometer to classify soil texture using factorial discriminant analysis, and reported 82% correct classification on the validation set. Christy (2008) built a shank-based spectrophotometer for real-time soil property sensing and reported that the best prediction was achieved for SOM content with R^2 of 0.67. The final purpose for sensing soil properties would be to develop a real-time in-situ sensing system. However, as Ge et al. (2006) pointed out, there would be many reasons that a real-time sensing system would not be possible due to great variabilities of soil properties. They reviewed different soil properties that were previously studied with different sensing platforms and data analysis techniques. There were also numerous groups who studied multiple soil properties using NIRS. Those properties include clay content, specific surface area, cation-exchange capacity, hygroscopic moisture, carbonate content, and organic matter content with R^2 values of 0.55–0.70 for validation (Ben-Dor and Banin, 1995); clay, carbon, and nitrogen contents with validation RMSE values of 2.9%, 0.06%, and 0.007%, respectively (Walvoort and McBratney, 2001); K, P, Ca, Mg, Na, Zn, clay, sand, and pH with R^2 values of 0.05–0.68 for prediction (Thomasson et al., 2001); 33 chemical, physical, and biochemical properties with R^2 values of 0.00–0.89 for prediction (Chang et al., 2001); total N, organic C, active N, biomass and mineralisable N and pH with R^2 values of 0.80–0.96 for validation (Reeves and McCarty, 2001)); exchangeable Ca, effective cation-exchange capacity (ECEC), exchangeable Mg, organic C, clay content, sand content, and pH with R^2 values of 0.67–0.88 for validation (Shepherd and Walsh, 2002); CEC, exchangeable Ca and Mg, pH and Ca:Mg ratio, organic carbon, and exchangeable sodium percentage with R^2 values of 0.18–0.90 for validation (Dunn et al., 2002); organic C, inorganic C, and total N with R^2 values of 0.85–0.96 for prediction (Chang and Laird (2002); pH, SOM, P, K, Ca, and Mg with R^2 values of 0.24–0.88 for validation (Lee et al., 2003); Ca, K, Mg, Na, P, Zn, clay, and sand with wavelet analysis with R^2 values of 0.16–0.69 for prediction (Ge and Thomasson, 2006); and clay, soil organic C, inorganic C, dithionate–citrate extractable Fe, cation exchange capacity (CEC), relative kaolinite content, and relative montmorillonite content with R^2 values of 0.73–0.91 for prediction (Brown et al., 2006).

There were groups of researchers who focused on utilizing spectral information in the MIR region (2500–50,000 nm). Ehsani et al. (2001) investigated soil diffuse reflectance in the MIR range to determine soil nitrate content using a Fourier Transform Infrared (FTIR) spectrophotometer. They identified a strong nitrate absorption peak at 7194 nm and estimated the concentration with R^2 values of 0.86–0.88. Merry and Janik (2001) demonstrated that MIR spectroscopy could rapidly analyze and predict soil properties (carbonate and organic carbon, total nitrogen, cation exchange capacity, some exchangeable cations, electrical conductivity, pH, soil texture, and a number of other properties) very well. McCarty et al. (2002) compared NIR (40–2500 nm) and MIR spectroscopy in detecting soil C (total, organic, and inorganic). They reported that MIR analysis outperformed NIR, suggesting high quality information available in MIR region. Linker et al. (2004) investigated direct estimation of soil nitrate content using Fourier transform infrared (FTIR) attenuated total reflectance (ATR) spectroscopy in MIR region and reported best root mean square prediction errors of 38–43 ppm-N based on different prediction methods. Jahn et al. (2005) applied wavelet analysis to soil FTIR ATR spectral data to estimate soil nitrate concentration, and reported that wavelet analysis was successful in predicting nitrate content with 6–10 ppm NO3-N standard errors for pooled data. Further Jahn et al. (2006) developed short-time Fourier transform (STFT) with soil FTIR ATR spectral data to minimize interferences from other ions and was able to reduce standard errors as low as 4 ppm NO_3-N. Viscarra Rossel et al. (2006) compared the performance of different wavelength ranges (VIS, NIR, and MIR) with the combined range. Prediction accuracy varied greatly depending on soil property.

Overall, VIS/NIR spectroscopy showed great potential in sensing different soil properties, and reached its blooming stage where real-time commercial detection systems have already been developed or is being currently developed for various operations in crop production.

7.2. Soil sensing using airborne and satellite imaging

There have been numerous studies using airborne and satellite imageries to detect different soil properties on a larger scale. In mid 1980s, Baumgardner et al. (1985) described applications of soil reflectance measurements for airborne and satellite based soil detection. Interestingly, they listed GIS as georeferenced information system (not "geographic information system"), which would be an emerging technology for soil data inventory and monitoring. Different satellite imageries were used for soil sensing such as SPOT (Agbu et al., 1990), and Landsat TM (Coleman et al., 1993). The analysis from SPOT imagery resulted in low correlation coefficients of less than 0.35 between different spectral bands and soil properties. Landsat TM images used by Coleman et al. (1993) yielded an overall 97% accuracy in differentiating the surface soils. They reported possible sources of error that contributed to the performance were atmospheric particles such as moisture, CO_2, dust, etc. However, color infrared digital orthophoto quadrangle (CIR-DOQ) imageries used yielded an overall accuracy of 63% in differentiating surface soils (Coleman and Tadesse, 1995). Njoku et al. (2003) described soil moisture retrieval approach and its implementation from the Advanced Microwave Scanning Radiometer (AMSR-E) on the Earth Observing System (EOS) Aqua satellite, launched in 2002.

Another application of the satellite imagery is the soil line, which is a linear relationship between bare soil reflectance observed in two different wavelengths. Galvao and Vitorello (1998) investigated the soil lines between conventional red and NIR bands for the influence of the chemical constituent and moisture in soil samples. Fox and Sabbagh (2002) also utilized the soil lines of bare soil images to map soil organic matter and provide guidance for soil sampling.

Aerial images were used for detecting soil P and organic matter (Varvel et al., 1999) and soil moisture (Muller and Decamps, 2000). Barnes and Baker (2002) used both multispectral airborne and satellite images to develop soil textural class maps. They observed that differences in field properties lowered the accuracy of spectral classification results; however reasonable accuracy was obtained when a field-by-field spectral classification was conducted. Further, Barnes et al. (2003) described remotely sensed data and ground-based sensing data for soil properties (soil organic matter, electrical conductivity, compaction, and nitrate level) and corresponding challenges for different sensing methods. They emphasized that the integration of multispectral imagery and ground-based sensor data could yield more accurate soil maps. Ben-Dor (2002) provided a detailed description on detecting soil properties using remote sensing, and described principles of quantitative remote sensing of soils, mechanisms of the soil-radiation interactions, potential problems, factors affecting remote sensing, and high spectral resolution (HSR) sensors. He emphasized that “sophisticated analytical method and a synergy between physical and empirical models” would be very important in retrieving soil property information from airborne reflectance measurements. He pointed out that near infrared reflectance analysis would be a very promising technology in detecting soil properties using remote sensing. Metternichta and Zinck (2003) reviewed techniques for sensing soil salinity using aerial photographs, satellite- and airborne multispectral sensors, microwave sensors, video imagery, airborne geophysics, hyperspectral sensors, and electromagnetic induction meters. They also discussed different feature recognition and mapping techniques including spectral unmixing, maximum likelihood classification, fuzzy classification, band ratioing, principal components analysis and correlation analysis.

7.3. Soil compaction

Soil compaction, as discussed by Hamza and Anderson (2005), causes many problems in crop production, including decreased water storage and supply, decreased soil physical fertility, reduced plant growth, reduced nutrient mineralization, reduced activities of micro-organisms, decreased crop yield, and increased wear and tear on cultivation machinery. Thus, soil compaction sensing is an important aspect of precision farming of specialty crops.

As an earlier study for soil compaction, Soehne (1958) studied pressure distribution in the soil under tractor tires with semi-empirical formulas developed by Froehlich (1934) using soil concentration factor, and explained the principles of static and kneading soil compaction. Freitag et al. (1970) studied the soil characteristics which are related to soil-machine problems using the concept of similar systems (i.e., a prototype and a model), described capabilities for carrying out useful similitude studies such as predicting response of a specific prototype and developing general soil-machine relations for special soil conditions, and presented future research directions in soil-machine systems. Wismer and Luth (1972) have developed useful equations that related tire characteristics and soil conditions to tractive performance such as wheel towed force, torque, and pull using soil strength, wheel load, slip, and tire size. They reported that these equations represented a major portion of soil-wheel interaction, and recommended these for computer simulation and “hand” analysis of off-road vehicles. Pitts (1980) investigated various models to predict the change in soil strength due to wheel traffic using soil cone index as an overall measure of soil strength, and identified that initial soil cone index, velocity of a vehicle, normal load, slip, and wheel width to diameter ratio were potential parameters that could affect the change in soil cone index.

To determine soil cutting resistance with depth, Glancey et al. (1989) designed and tested an instrumented chisel to study force distribution and soil fracture mechanics, and reported that the device was able to estimate soil cutting force distribution over tillage depth and to detect soil fracture modes. Starting in early 2000s, there have been considerable efforts on developing sensing systems for soil compaction. Adamchuk et al. (2001) designed a vertical smooth blade to measure the mechanical impedance of soil at multiple depths and to estimate resistance pressure. In laboratory tests, a close relationship ($R^2 = 0.99$) between measured and calculated strain was found and in field experiments an R^2 of 0.95 was obtained between the estimated vertical smooth blade resistance and cone penetrometer resistance. Chung et al. (2003) developed an on-the-go soil strength profile sensor using load cells. Then, Chung et al. (2004) evaluated the sensor and reported R^2 values of 0.61 and 0.52 to estimate prismatic soil strength index for a claypan soil field and a floodplain soil field, respectively. Adamchuk et al. (2004a) provided a review of different sensing technologies for soil mechanical, physical and chemical properties using electrical and electromagnetic, optical and radiometric, mechanical, acoustic, pneumatic, and electrochemical measurement methods. They reported that among these, only electric and electromagnetic sensors have been mostly used and that the commercial sensors need to provide direct inputs to existing prescription algorithms. They described that the soil maps obtained by the sensors should also have an economic value. Adamchuk et al. (2004b) developed a prototype instrumentation system for variable-depth tillage using load cells and strain gauges. Models for linear pressure distribution were used to compare its performance with a standard cone penetrometer measurement. Andrade et al. (2004) evaluated an improved version of a soil compaction sensor and tested it in two commercial fields. They compared the sensor measurement with cone index data and reported correlation coefficients of 0.23–0.70 at different locations and depths. Mouazen and Ramon (2006) developed an online system for measuring soil draught, cutting depth, and moisture content, and discussed the relationship among them. Adamchuk and Christenson (2007) developed an instrumented blade to map soil mechanical resistance as a second-order polynomial with an array of four strain gages. Andrade-Sanchez et al. (2007) developed and evaluated a soil compaction profile sensor and reported that the soil cutting force was influenced by soil bulk density, moisture content, and the location of the cutting element within the soil profile, and that the sensor measurements agreed with the cone index profile with an R^2 of 0.977. Andrade-Sanchez and Upadhyaya (2007) reported the development of the UC Davis soil compaction profile sensor and a relationship between its measurements and reference values obtained with a standard cone penetrometer. Further Andrade-Sanchez et al. (2008) made significant changes in the sensor geometry over the previously developed soil compaction profile sensor and evaluated it in commercial fields. They reported that the device was able to produce soil cutting resistance variability map. Chung et al. (2006) developed a soil strength profile sensor (SSPS) using load cells and reported that the optimum extension and spacing of the cutting tips were 5.1 and 10 cm, respectively.

Also they reported that the sensor measurements had a linear relationship with the penetrometer cone index with a slope of about 0.6. Sudduth et al. (2008) compared the two previously developed on-the-go soil compaction sensors (soil compaction profile sensor and soil strength profile sensor) in field testing. They reported that the soil compaction measured by the two sensors in MPa was similarly affected by soil strength variations in the testing sites, and that soil compaction maps generated by the two sensors showed similar patterns with more spatial details than cone index maps alone. Hemmat and Adamchuk (2008) reviewed previous research on different sensors for soil strength, profile, fluid permeability, and water content. They suggested that the fusion of different sensors would be the next step in mapping spatially variable soil physical properties. Tekin et al. (2008) developed a soil penetrometer that can generate 2D/3D soil compaction maps, tested in field conditions, and reported that the developed system could be used to determine soil compaction distribution at different depths. Mouazen and Ramon (2009) described modification of an on-line soil compaction prediction model and reported that soil compaction for the selected textures can be measured on-line using the bulk density model, and that the correction factor along with the bulk density model can be used for on-line soil compaction measurement.

7.4. Electrodes

A relatively newer method for sensing soil properties is based on the use of electrodes. In an earlier study, Adsett and Zoerb (1991) explored the feasibility of measuring soil nitrate levels using a nitrate-selective electrode and reported that ion-selective electrode technology could be adopted to automatically monitor in-field soil nitrate content. However, the calibration procedure may be unsuccessful when the electrodes or the operating environment is not in an equilibrium state. Adsett et al. (1999) further developed an automated soil nitrate monitoring system consisting of a soil sampler, a soil metering and conveying unit, a nitrate extraction unit, and an electronic control unit. They reported that the system was successfully tested in a laboratory, however more work would be needed for in-field use since some mechanical and electrical problems were found including clogging of the extractor outlet. Adamchuk et al. (1999) started utilizing electrodes in sensing different soil properties extensively. They developed an on-the-go soil pH sensing system using an electrode and reported an R^2 of 0.83 and standard error of prediction of 0.45 pH in field testing. Birrell and Hummel (2000) utilized PVC matrix ion-selective membranes that are compatible with ion-selective field effect transistors (ISFETs) to measure soil nitrate contents, demonstrated their sensitivity and selectivity, and reported that the ISFETs could be used to develop a real-time in-field sensor system. Birrell and Hummel (2001) then tested a multi-ISFET sensor and found that the sensor was able to successfully measure soil nitrate content in solutions manually extracted with a proper calibration solution, however was not successful for an automated soil solution extraction system. Brouder et al. (2003) developed a rapid and inexpensive ion selective potassium electrode, evaluated its performance, and investigated its sensitivity to environmental variables. Adamchuk et al. (2006) tested the soil pH measurement system in artificially created areas and reported a standard error of 0.38 pH. Kim et al. (2006) evaluated nitrate and potassium ion-selective membranes and investigated their effect on soil extractants. They reported that the membranes showed linear response with nitrate and potassium concentrations, however, their sensitivity decreased at lower concentrations (less than 10–4 mole/L). Then, Kim et al. (2007a) studied different ion-selective electrodes (ISE) for sensing phosphate and found that cobalt rod-based electrodes showed sensitive response over a typical phosphorus concentration range in agricultural fields. Kim et al. (2007b) further expanded the applications of ISE to simultaneous measurement of soil macronutrients (N, P, and K). They reported that the NO_3 ISEs yielded similar results to those from standard laboratory tests (R^2 = 0.89), however K and P ISEs estimated 50% and 64% lower concentrations than the standard laboratory analysis, respectively. Sethuramasamyraja et al. (2007) expanded the ion-selective sensing system to map simultaneously soil pH, residual nitrate (NO_3^-), and soluble potassium (K^+) contents. They reported that besides the soil type, the soil/water ratio affected sensor performance the most. Adamchuk et al. (2007) compared soil pH maps created by the on-the-go sensing system with the results from grid sampling, and reported that field-specific calibration would be needed to increase accuracy. Sethuramasamyraja et al. (2008) evaluated an Agitated Soil Measurement (ASM) method for soil pH, soluble potassium and residual nitrate contents using ion-selective electrodes and an integrated Agitation Chamber Module. They reported that calibration parameters for pH and K electrodes were stable, however those for nitrate drifted significantly. The test results showed the potential for on-the-go soil property mapping even though improvement would be needed. Currently some commercial electrodes are available for measuring soil properties such as moisture, pH, nitrate, potassium, bromide, and chloride by London-Phoenix Company, Cole-Parmer, and Zhejiang Top Instrument Co. Ltd.

7.5. Microwave technique

There are two different methods in microwave soil moisture sensing: passive and active. Passive microwave was also used to detect soil properties, particularly soil moisture. Schmugge (1978) presented different remote sensing methods of the moisture content in the soil surface by using the thermal and dielectric properties of water, and presented three different methods to detect soil moisture: thermal IR approach, passive microwave sensing and active microwave sensing. Later, Jackson and Schmugge (1989) reviewed soil moisture sensing methods using passive microwave and presented potential applications. They concluded that the future remote sensing of global soil moisture would depend on the final configuration of the Earth Observation System (EOS). Njoku and Entekhabi (1996) discussed basic principles of passive microwave remote sensing of soil moisture. It was found that the emission of thermal microwave radiation from soil was highly correlated with soil moisture content. Microwave methods also had the added advantage of being unaffected by cloud cover and highly accurate in the case of barren soil or soil with low vegetation cover. They mentioned that incorporation of passive microwave data into hydrologic models would be promising. Vinnikov et al. (1999) used a scanning multichannel microwave radiometer (SMMR) for estimating soil moisture content over large regions. The results showed that the polarization differences as well as the microwave emissivity were highly correlated with soil moisture information in regions with sparse or no vegetation. The system was very useful as it eliminated the need for the expensive direct moisture measurement methods used.

Guha et al. (2003) implemented passive microwave measurements at 1.4 GHz using an electronically scanned thin array radiometer to measure soil moisture and reported a good agreement between measured and predicted soil moisture content. Tien and Judge (2006) discussed the effect of changing soil temperature and moisture on measured brightness temperatures over a growing season of cotton, and reported that the measured and predicted sensitivities of the brightness temperature (T_B) to the changes in soil moisture at 4 cm in the early growing season corresponded well to each other. Tien et al. (2007) investigated different calibration techniques for ground-based C-band radiometers by comparing the measured T_B with the estimated, and reported

Table 2
Comparison of different microwave sensing techniques for soil moisture content.

Method	Advantages	Disadvantages/challenges	Common features
Active	Better spatial resolution than passive	Need a radar as a microwave source	Very sensitive to soil water content in the top few centimeters
	Availability of measurement	Very sensitive to the roughness of soil surface and geometry and structure of vegetation, which makes soil water content estimation difficult	Independent of solar radiation, clouds, and light rain, and not affected by atmospheric conditions
		Poor temporal resolution	Measure radiation quantities that are functions of the soil's index of refraction
			Seasonal variation in relationships between microwave remote sensing and soil water content needs further investigations
			Lack of combined active/passive observations at various spatio-temporal scales
Passive	No signal source is required	Poor spatial resolution	
	Better temporal resolution		
	More widely used than active sensing, since it is less sensitive to roughness of soil surface and geometry and structure of vegetation		

the mean absolute temperature error of 2–4 K. Judge (2007) provided a brief review of measuring soil moisture using microwave remote sensing, which utilizes the difference in the refractive indices of soil and water. Measuring near surface soil moisture content can be done through semi-empirical models, a microwave model with a hydrologic or crop model, and combined use of passive and active observations through various techniques, however some major technical challenges exist such as lack of satellite-borne radiometers operating at wavelengths near 20 cm, and seasonal variations in relationships between microwave remote sensing and soil water. Table 2 summarizes the differences and common features of active and passive microwave soil moisture sensing.

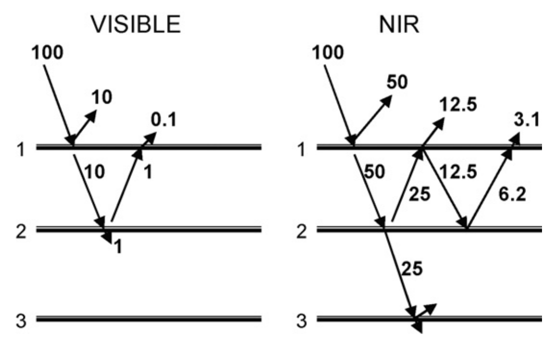


Fig. 7. Schematic illustration of reflectance and transmittance of radiation through crop layers (horizontal numbered lines) in the visible and NIR regions respectively (source: www.geo-informatie.nl/igi-new/literature/Ch07_IGI_RS_Spectr_Sign.doc).

8. Foliar disease detection

8.1. Why should foliar diseases be detectable?

There are strong indicators that plant diseases are automatically detectable. The detection information carriers considered in this paper are electromagnetic waves. The hypothesis is that healthy plants interact (absorb, reflect, emit, transmit and fluoresce) with electromagnetic radiation differently than infected plants.

Plants show different optical properties. Some of them can be seen by the naked eye, others are obvious using advanced equipment. Light measurement techniques are very helpful for detecting these properties.

Disease detection based on spectral reflection information relies on the properties of the light emerging from the canopy after multiple interactions, i.e., reflections, transmissions, and absorptions, with the tissues of the plant. This diffusely reflected radiation forms the canopy spectral signature, a function described by the ratio of the intensity of reflected light to the illuminated light for each wavelength in visible (VIS = 400–700 nm), near-infrared (NIR = 700–1200 nm) and shortwave infrared (SWIR = 1200–2400 nm) spectral regions. Leaf reflectance is defined as the proportion of the irradiated light reflected by the leaf. The interaction of electromagnetic radiation with plants varies with the wavelength of the radiation. Healthy leaves typically exhibit:

- Low reflectance at VIS wavelengths due to strong absorption by photoactive pigments (chlorophylls, anthocyanins, carotenoids). In Fig. 7, one can observe how visible irradiation is absorbed by the canopy and very little radiation is released, especially from the lower canopy layers.
- High reflectance in the NIR due to multiple scattering at the air-cell interfaces in the leaf internal tissue.
- Low reflectance in wide wavebands of the SWIR due to absorption by water, proteins and other carbon constituents (Jacquemoud and Us, 2001; Wooley, 1971).
- Due to their high water content (emissivity between 0.97 and 0.99), healthy leaves behave much like "black bodies" and emit radiation in the thermal infrared band (TIR ≈ 10 μm) according to their temperature.

Alterations of the reflectance can be considered as an inference of a leaf compositional change. Diseases can affect the optical properties of leaves at many wavelengths, thus disease detection systems may be based on spectral measurements in different wavebands or a combination of wavebands. Healthy plants appear green since the green light band (ca. 550 nm) is reflected relatively efficiently compared to blue, yellow and red bands, which are absorbed by photoactive pigments. Diseased plants usually exhibit discrete lesions on leaves, corresponding to necrotic or chlorotic regions, which increase reflectance in the VIS range, especially in the chlorophyll absorption bands. In particular, reflectance changes at wavelengths around 670 nm, cause the red edge (the sharp transition in the reflectance spectrum from low VIS reflectance to high NIR reflectance that generally occurs around 730 nm) to shift to shorter wavelengths. Conversely, biomass reduction linked to senescence, reduces growth and defoliation and decreases the canopy reflectance in the NIR band.

Images, as obtained using regular cameras, are two-dimensional slices representing scenery in one (monochromatic) or more (multispectral) spectral regions. Typically, RGB-images represent a red, a green and a blue waveband, similar to human vision. Images in other wavebands can be acquired as e.g., with a Color Infrared (CIR) camera. It provides multispectral images with some true-color sensitive wavebands, as well as a NIR waveband. Representation is possible using separate black-white images or false color images.

Thermography is a technique that acquires images of thermal radiation (radiation between 3 and 100 μm). The object under investigation emits a certain thermal radiation depending on the temperature of this object and its emissivity. Plant temperature can be estimated through the thermal radiation captured by a thermal camera and the emissivity of the plants. This temperature is highly correlated with the stomatal conductance of the plants. When the leaf stomata close during an illumination event, CO_2 and H_2O are not exchanged which causes a greenhouse effect in the leaf. During a high thermal radiation event (e.g., solar illumination, halogen illumination, etc.), a global increase of the leaf temperature can be expected. Plants under water stress are known to close their stomata and therefore increase their temperature.

Finally a lot of information about the metabolic status of the plant can be obtained by the artificial excitation of the photosystems of a plant and the observation of the relevant responses. The most relevant technique described here is fluorescence. Fluorescence is light emitted during absorption of radiation of some shorter wavelength. The typically fluorescing part of the plant is the chlorophyll complex. Irradiating the chloroplasts with blue or actinic light will result in some re-emission of the absorbed light by the chlorophyll. The proportion of re-emitted light compared to the irradiation is variable and depends on the plant's ability to metabolize the harvested light. In so-called dark-adapted leaves, photosynthetic activity is quasi-zero. The plant respires (gain energy ATP) through mitochondrial activity. When suddenly bombarded with a very strong blue light beam, the Light-Harvesting Complexes (HCL) of the chloroplasts becomes completely saturated. At that moment the excited chlorophyll cannot release its excitation energy since the metabolic pathways for photo-assimilation have not yet been started. Therefore the plant chlorophyll will need to discharge its excess excitation energy into lower energy photons, which is observable as red emission. Clearly this fluorescence depends upon the concentration of chlorophyll and is a first good indicator of the plant's capacity to assimilate actinic light. Moreover, combining an actinic light source with brief saturating blue pulses, it is possible to estimate the plant's efficiency of photo-assimilation, Non-Photochemical Quenching (this is a measure of the thermal dissipation of the excited energy) and other physiological plant parameters.

Any disease that causes sufficient plant stress to distort the reflectance characteristics of crop foliage is a candidate for detection by means of remote sensing. As early as in the late 1920s, Taubenhaus et al. (1929) used an ordinary hand-held camera equipped with panchromatic film to take photographs of cotton fields infested by cotton root rot from an airplane. The black-and-white photographs were used to locate Phymatotrichum root rot spots of various sizes and shapes within the fields. Nevertheless, the stimulus for more recent development of aerial photography for crop disease detection came after Colwell (1956) conducted a number of experiments to study spectral reflectance properties of healthy and stressed cereal crops and to determine the optimum film and filter combinations for detecting and identifying certain cereal crop diseases such as black stem rust in wheat and oats and yellow dwarf virus in oats. Since then, numerous studies have been undertaken to link the spectral response of a particular disease to its appearance on aerial photographs.

Myers (1983) reviewed studies on the use of aerial photography for detecting potato late blight, clitocybe root rot of pecans, bunch disease of pecans, phony disease of peaches, corn leaf blight, bacterial blights and root rot in beans, and root rot in cotton and alfalfa fields. Ryerson et al. (1997) reviewed more aerial photographic studies grouped by four major types of crop diseases: airborne, seed-borne, insect-borne, and soil-borne. In addition to the above diseases mentioned, they reported that aerial photography has been successfully used to detect the following diseases: yellow rust of wheat, stem canker in rape, leaf spot and rust of the sugar-bearing crops of beet and cane, mold and dwarf-mosaic virus in corn, virus yellows in sugar beet, barley yellow dwarf virus in winter wheat, barley yellow mosaic virus, take-all in winter wheat, docking disorder root infection in sugar crops. Johnson et al. (2003) investigated the spatial and temporal dynamics of late blight from color-infrared (CIR) aerial photographs of five commercial potato fields and they concluded that aerial photography coupled with spatial analysis was an effective technique to quantitatively assess disease patterns in relatively large fields and was useful in quantifying an intensification of aggregation during the epidemic process on a large scale.

Although aerial photography has been the primary remote sensing technique used for study of crop diseases, multispectral and hyperspectral electronic imaging systems have also been used for this purpose. Cook et al. (1999) demonstrated the potential of airborne CIR video imagery for detecting Phymatotrichum root rot and the root-knot nematode in kenaf. Fletcher et al. (2001) used airborne digital imagery for detecting Phytophthora foot rot infections in citrus trees. Apan et al. (2004) demonstrated that Hyperion satellite hyperspectral imagery can be used to detect the orange rust disease in sugarcane. Du et al. (2004) evaluated the potential of airborne multispectral and hyperspectral imagery for detecting citrus greasy spot. Zhang et al. (2005) used an airborne multispectral imagery with four broad bands (blue, green, red and NIR) to map late blight infestations in two tomato fields. Chen et al. (2007) used Landsat multispectral imagery to successfully detect the severe infestation of the take-all disease in wheat. Franke and Menz (2007) evaluated high resolution QuickBird satellite multispectral imagery and airborne HyMap hyperspectral imagery for detecting powdery mildew and leaf rust in winter wheat and their results showed that high classification accuracies were achieved when the infection was severe at the late crop growth stages.

Airborne and spaceborne imagery has been successfully used to detect and map a large number of crop diseases, but early detection remains difficult and in some cases impossible. In most cases, by the time disease symptoms can be detected on the remote sensing imagery, damage has already been done to the crop. For some diseases, this may be early enough to take control measures in order to minimize damage; for others, it may be too late to correct the problem within the growing season. In fact, remote sensing imagery has been primarily used to assess the extent and intensity of the damage caused by disease. In this regard, remote sensing is a very cost-effective tool.

Moreover, remote sensing image data obtained in the current growing season can be useful for the management of reoccurring diseases, such as soil-borne fungi, in the following seasons. Another challenge for remote sensing detection of crop disease is that multiple biotic and abiotic conditions may coexist and produce similar effects on the color, geometry, or vigor of the upper crop foliage. Crop diseases and insects and some soil problems can cause morphological (wilting or stunting) and physiological (chlorosis, darkening, or dehydration) changes in a crop. If only one dominant disease occurs or if multiple diseases or stresses with distinctive symptoms are present, remote sensing imagery

Table 3
Overview of the different remote plant sensing techniques and which radiation wavebands are involved.

Technique	Measurement waveband
Reflection based sensing:	
• Spectral reflectance	450–2100 nm spectrum
• Imagery:	
Monochromatic (images in 1 waveband)	Any combination of monochromatic wavebands
Multispectral e.g., RGB, CIR (images in multiple wavebands)	
Emission based sensing: thermography	Shortwave thermography: 3–5 μm
	Longwave thermography: 8–15 μm
Fluorescence	
• Blue excitation (350–420 nm)	690 nm

will be able to discriminate the infected areas; otherwise, discrimination of the diseases may be possible with additional knowledge of the dynamic behaviors of the diseases or other stresses and relevant information of the specific soil and crop conditions. Moreover, high spatial resolution multispectral and/or hyperspectral imagery taken at multiple times may be necessary. As remote sensing imagery is becoming more available and less expensive, it will present a great opportunity for both growers and researchers to more effectively use this data source for the detection of crop diseases. Many crop diseases have been identified as good candidates for remote sensing, but practical procedures for farming operations are still lacking. Efforts need to be devoted to the development of operational methodologies for detecting and mapping these candidate diseases. Meanwhile, more research is needed to evaluate more advanced imaging systems and image processing techniques for distinguishing the diseases that are difficult to detect or occur with other stresses.

8.2. Potential spectral techniques for disease detection

The basic techniques discussed in this paper for sampling non-contact information about the status of plants are illustrated in Table 3.

8.3. Disease detection using light reflection

As the primary effects of different diseases vary (chlorophyll, water and temperature effects), different wavebands are suitable for detection of different diseases (Bryson et al., 1998; Dudka et al., 1998).

For example, reflectance changes in violet-blue and NIR wavebands (380–450 nm and 750–1200 nm) were used to detect early infections of cucumber leaves by the fungus, *Colletotrichum orbiculare* (Sasaki et al., 1998). Later, when visual symptoms appeared, infections were characterized by reflectance changes in chlorophyll absorption bands (470 nm and 670 nm) and, with lower significance, in NIR reflectance. Polischuk et al. (1997) used spectral reflectance measurements to make an early diagnosis of symptoms in *Nicotiana debneyi* plants at different stages of tomato mosaic tobamovirus infection. Reduction in chlorophyll content in the leaves could be detected by reflectance measurements within 10 days after inoculation even though significant visible differences between the control and the infected plants were not noted until after three weeks. While evaluating seven disease assessment methods for downy mildew in quinoa, Danielsen and Munk (2004) found that reflectance measurements in the red (640–660 nm) and NIR (790–810 nm) wavebands could provide highest correlation with yield loss. This is explained by its ability to measure pathogen-induced defoliation. Reflectance of tall fescue within the 810-nm band exhibited the strongest relationship ($19\% \leq R^2 \leq 63\%$) with visual severity estimates of *Rhizoctonia* blight and gray leaf spot (Green et al., 1998). Hyperspectral AVIRIS data were taken from *Phytophthora infestans* infested tomato fields by aerial imaging (Zhang et al., 2002). Furthermore, Zhang et al. (2003) sorted out that the spectral reflectance of the NIR region, especially 0.7–1.3 μm, was much more valuable than the visible range to detect crop disease. Malthus and Madeira (1993) studied the spectral effect of field bean (*Vicia faba*) leaves infected by the necrotrophic fungus *Botrytis fabae*. Infestation caused reduced photosynthesis, attributed to a decreased stomatal conductance. However, no changes in spectral reflectance were evident before visual symptoms were observed. The most significant changes in spectral reflectance associated with the disease were a flattening of the response in the visible region and a decrease in the near-infrared reflectance shoulder at 800 nm. Both these responses may be attributed to collapse of leaf cell structure as the fungus spread. Muhammed and Larsolle (2003) concluded that the fungus *Drechslera tritici-repentis* mainly affected the spectral signature by: (1) a flattening of the green reflectance peak together with a general decrease in reflectance in the near-infrared region and (2) a decrease of the shoulder of the near-infrared reflectance plateau together with a general increase in the visible region between 550 and 750 nm. Devadas et al. (2009) concluded that in order to discriminate between different wheat rust species there was a need to apply a combination of different spectral indices as it was impossible to achieve high discrimination performance by using isolated indices. A sequential application of firstly the Anthocyanin Reflectance Index (ARI) to separate healthy, yellow rust and mixed stem rust/leaf rust classes followed by the Transformed Chlorophyll Absorption and Reflectance Index (TCARI) to separate leaf and stem rust classes could provide a means of wheat rust species discrimination. Huang et al. (2007) showed that the Photochemical Reflectance Index (PRI) was a very a robust spectral index for quantifying yellow rust infection. The effectiveness of PRI was explained by the fact that it is highly correlated to biomass and foliar nitrogen content and rust incidence is generally negatively correlated.

However, disease presence can also indirectly be estimated. Based upon 810 nm canopy reflectance models, variations in alfalfa yield and LAI could be 12–15% better explained than using percentage defoliation through visual assessment as independent variable (Guan and Nutter, 2002). Defoliation was due to foliar disease epidemics and the absence of fungicide spray. The relation between NDVI (Rouse et al., 1974), red reflectance variations from airborne imaging sensors and yield and vine density variations in cranberry fields has been investigated in Pozdnyakova et al. (2002). The major cause of variation was found to be *Phytophthora* root rot disease.

When plants are eaten by insects, these plants will die off very rapidly and senescence occurs, explaining the radical spectral changes observed by Yang and Cheng (2001). The authors discovered a very high dependency of the blue, red and NIR spectral regions to infestation of brown planthoppers in rice, meanwhile green regions were completely insensitive. As planthoppers eat the rice leaves, the question here is whether the measured spectral signature is purely pest related, or a mixture in which radiation from soil and senescent leaves increases with infestation intensity. Riedell and Blackmer (1999) obtained similar results for wheat infested with aphids, in particular greenbugs (*Schizaphis graminum Rondani*) and Russian wheat aphid (*Diuraphis noxia Mordvilko*).

An important result regarding early detection of viral diseases is presented in Naidu et al. (2009) who have shown that it is possible to detect the presence of the grapevine leafroll disease (GLD) even at a presymptomatic stage. This was mainly due to the negative effect of the virus infection on the physiology of the plant resulting in metabolic and pigment changes. Although visible changes

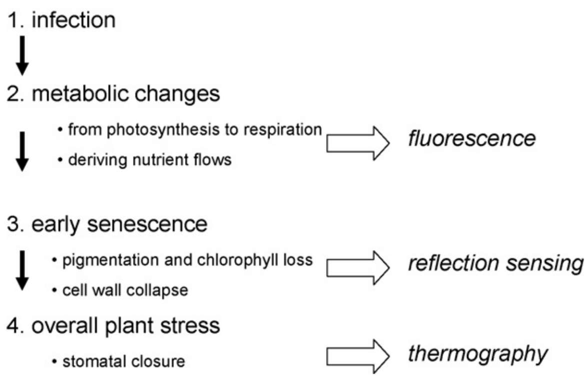


Fig. 8. Illustration of the relevant measurement techniques during the infection of a foliar disease, related to what these techniques monitor.

in leaf color were more apparent in symptomatic than in non-symptomatic leaves, leaf reflectance measurements could provide specific reflectance parameters (in the form specific combinations of indices and reflectance bands) for detection of GLD during both non-symptomatic and symptomatic stages of the disease in red-berried cultivars.

In summary, the effectiveness of disease detection techniques that are based on light reflection depends on a number of factors, namely changes in concentrations of non-chlorophyll pigments, extent of chlorophyll degradation and on the spectral characteristics of the infected leaf areas. At early stages of infection, discriminating features that incorporate NIR reflectance are expected to be less efficient, owing to the time lag between infection and breakdown of internal leaf structure. Therefore, the stage of the disease and the spread of the symptoms is a crucial factor affecting the capability of disease detection and infection quantification based on techniques that rely on light reflection.

8.4. Disease detection using fluorescence

The visible light absorbed by leaf pigments is partially used to drive photosynthesis and partially dissipated as fluorescence, re-emitted at VIS-NIR wavelengths (peak emission at 690 nm) and as radiative heat in the TIR region. Although affected by the intensity of the incident light and the normal functions of the leaf, these de-excitation processes occur in competition with photosynthesis; hence, fluorescence and thermal sensing can be used as indirect methods to probe the photochemical efficiency of a plant, i.e., its health status.

In general, plants react quickly to stress factors, such as disease, by decreasing photosynthesis, thus increasing fluorescence and heat emissions (Scholes, 1992; Wright et al., 1995). For example, Daley (1995) found sub-millimeter sized high fluorescence emission spots that corresponded with TMV infection points on tobacco leaves. Similar patterns were found on bean leaves infected by bean rust (Peterson and Aylor, 1995). Bodria et al. (2002) observed fluorescence spots, with intensity significantly higher than healthy tissue, on wheat leaves 2-3 days after inoculation with Brown rust spores (*Puccinia recondida*), i.e., 3–5 days before the first visual symptoms appeared (see also Fig. 8).

Decrease in photosynthesis also affects fluorescence kinetics. Scholes and Rolfe (2003), who studied the effects of crown rust on oat leaves, discriminated infected and healthy regions by differences in the emission kinetic curves. Similarly, Abutilon mosaic virus could be detected on leaves of Abutilon striatum (Osmond et al., 1998).

In addition to changes in fluorescence kinetics, the spectrum of light that fluoresces from diseased plants is different from that from healthy plants, with a significant decrease of relative intensity in the blue and green bands compared to red and NIR bands (Buschmann and Lichtenthaler, 1998; Ludeker et al., 1996).

In summary, although in general, changes in fluorescence emission do not provide a precise and clear indication of specific stress factors, fluorescence does enable anticipation of disorders in plants, notable disease symptoms, since the photosynthetic process is affected before tissue modifications occur.

8.5. Disease detection by thermography

Stress factors can also change the thermal properties of plants, influencing emissions in the TIR band, mainly through effects on the water status of leaves (Berliner et al., 1984; Mottram et al., 1983; Pinter et al., 1979). For example, stress can induce stomatal closure resulting in an increase in leaf temperature, detected by thermal imaging, often at an early stage of infection (Lindenthal et al., 2005; Chaerle et al., 1999; Omasa, 1990). Spots of higher temperature were detected on the leaves at the infection points. Oerke et al. (2005) detected a remarkable temperature decrease (up to 1 °C) of a downy mildew infection (*Pseudoperonospora cubensis*) on cucumber leaves as well as an apple cab fungus infection (*Venturia inaequalis*) on apple leaves. This decrease was due to a local increase in water loss, since the disease ruptured the cuticle. After a longer infection period, the overall temperature of the leaves increased. However, presence of disease affected temperature only slightly. These last four authors investigated thermography in temperature controlled environments.

Lili et al. (1991) observed the thermal effects of eyespot (*Tapesia yallundae*) and cereal cyst nematode (*Heterodera avenae*) infections in winter wheat and suggested that the diseases could be detected and mapped using aerial instant thermal imagery. This method was later applied by Nicolas (2005) for detecting *Septoria tritici* infections in winter wheat. Only when the highest wheat leaves were infected, the temperature difference between healthy and diseased canopies started to increase.

Leinonen and Jones (2005) reported the feasibility of thermography for estimating the presence of stress on grape-vine canopy at a proximal distance of about 1 to 2 m. They pointed that sunlit leaves showed a higher average temperature than shaded leaves. Therefore the different leaves needed to be separated by using a visual reflection camera. Both thermal and visual cameras were collimated on the same field of view. The complexity of such an approach increases when topographical plant height differences increase, e.g., in wheat.

In summary, looking at temperature differences is an indirect method for monitoring crop stress. The only successful investigation at a field scale (Nicolas, 2005) needed aerial imaging for capturing thermal radiation when the entire field was equally illuminated. Rapidly changing environmental factors, such as cloudiness, wind and eventual rainfall prohibit reliable in-field disease detection by thermography at a proximal distance (1–2 m).

8.6. Relevant optical properties for disease detection

The main relevant measurement techniques for detecting foliar infections are briefly represented in Fig. 8. During the earliest infection stages fluorescence is the most appropriate technique since it samples the health status in terms of photosynthetic efficiency. Following the initial metabolic changes, the fungus spreads radially around its infection point. The initial infection area necroses: it looses pigmentation, the photosynthetic apparatus is dissembled and the cell walls collapse. At this moment infection patterns become visible.

Analysis of the light reflection can help in detecting the infections from this stage onwards. Pathogen propagules can be detected in the VIS (depending on the pathogen); chlorophyll degradation in

Table 4
Overview of different sensor technologies for disease detection in the field.

Sensor technology	Advantages	Disadvantages	Best potential use
Fluorescence	Early stage disease detection even before tissue modifications occur	Cannot provide a clear indication of specific stress factors, medium detection accuracy, accuracy sensitive to light intensity	As an early alarm, anticipation of disorders in the future, laboratory use or night conditions
Light reflection	Can provide a clear indication between stress factors, high recognition accuracy of diseased plants	More effective after symptoms and discoloration become visible. Sensitive to control intensity, discoloration and age	For disease and other stress recognition in the greenhouse and in the field, to discriminate between different stress types
Thermography	Can detect disease infestation if this has affected the water status of the leaves, more effective for airborne remote sensing	Highly dependent on illumination, very low accuracy in changing weather conditions, sensitive to leaf coverage, cannot provide a clear indication of specific stress factors	In the greenhouse or for airborne sensing when illumination conditions are uniform and the ambient temperature is kept constant

the VIS and red-edge (550 nm; 650–720 nm); senescence in the VIS and NIR (680–800 nm) due to browning and SWIR (1400–1600 nm and 1900–2100 nm) due to dryness; changes in canopy density and leaf area in the NIR.

While the disease gradually takes control over the entire plant, it will show a global stress, which conducts to a general closure of the stomata, in view to reduce water losses. This change in transpiration can be monitored by thermography. However, the global leaf temperatures are rapidly changing, and are heavily dependent upon ambient temperature, illumination and wind. Therefore, due to changing environmental factors, thermography gives poor results when used on proximal sensing platforms.

The reviewed techniques give more reliable detection results when diseases are fully developed and infestations are high. Clearly, some changes in the spectral characteristics of plants provide the potential for using optical signals to detect the presence of diseases in agricultural crops.

The effectiveness of disease detection depends on the data processing algorithms that are used. For each crop-disease system, hyperspectral imaging methods can be used to simplify and automate disease detection. This can be based on simple formulae, algorithms or done by neural networks, e.g., Moshou et al. (2004), and Bravo et al. (2003) used image analysis algorithms to discriminate between background and wheat canopy (based on reflectance at 675 nm and 750 nm) and then by classification of combinations of spectral wavebands to discriminate between healthy leaf tissue and yellow rust disease lesions in winter wheat (West et al., 2003). Further improvement resulted from multisensor fusion of spectral and fluorescence features (Moshou et al., 2005) where a spectrograph provided a combination of reflectance intensities at selected wavebands. In the same paper, these data were combined with lesion indices resulting from fluorescence imaging of the same plants. The advantages, disadvantages and the best potential use of the presented sensor technologies are shown in Table 4.

9. Radio-frequency identification (RFID)

9.1. RFID technology

Recent outbreaks of food borne diseases like *E. coli* and *Salmonella* in fresh produce (spinach, green onions, and tomatoes) have reduced consumers' confidence in the safety of the specialty crops supply system (Buzby and Frenzen, 1999). In addition, the globalization of the world economy and free trade in agricultural products has promoted the flow of food products across national and regional borders, which enhances the possibility of wide spread of food borne diseases. Consumers and other stakeholders in the food supply chain demand greater assurance and transparency on the quality and safety of fruits and vegetables, as well as the impact of food production on the environment and ecology (Opara and Mazaud, 2001). Food traceability is defined as the ability to trace the history of a food product including its origin, growing practices, and the source of inputs (Langan, 2000). The RFID has become popular in recent years for the identification of items in the management of global supply chain. It is the most promising technology that can be used in the traceability of fruits and vegetable production supply chain.

RFID stands for radio-frequency identification which is a technology for automatic identification and it uses the RFID tags to store and retrieve data remotely. It emerged as a new technology for identification in 1970s, and it has gained much attention and developed in the past two decades (Want, 2003). The most visible application of RFID is probably the automatic toll payment systems at toll plazas to scan tags attached to the windshields of passing cars.

Typically, an RFID system consists of RFID tags, a reader, and a computer for database management. The RFID tag can be attached to or embedded into a product, animal, or person for the purpose of identification using radio waves. Each tag consists of an antenna connected to the silicon chip and encapsulated inside a module. Some tags can be read from several meters away and beyond the line of sight of the reader (Want and Russell, 2000).

Usually, the RFID tags can be classified into passive and active RFID tags. The major difference is whether the RFID tags have the internal power supply or not. The active RFID tags have their own internal power source to power the integrated circuits and to broadcast the response signal to the reader. Although the communications from active tags to readers is typically much more reliable, the active RFID tags are generally bigger and more expensive caused by battery volume and battery price.

Unlike the active RFID tags, the passive RFID tags requires no batteries and they can be intermittently powered from a distance by a reader that broadcasts energy to it. The tag exchanges information with the reader. This greatly reduces the size, price of the tag, as well as the related maintenance. The RFID tag can store non-volatile data through writable EEPROM and the data not only include the ID number, but also include other important information like the origin and growing information about the product. Because of its small size, lower cost, and free maintenance, the passive RFID tags have the great promise to be used in the specialty crops postharvest industry (Finkenzeller, 2003).

9.2. RFID application in specialty crops and agriculture production

Pesticides and herbicides could pose the threat to human health and the environment. The conventional paper-based record keeping of these agrochemicals is not very reliable and subject to human errors and bias. A study was conducted to investigate using the RFID tag to identify and verify agrochemicals in traceability systems (Peets et al., 2007). It was suggested that the most feasible approach is to store only minimum essential information on RFID labels and utilize a database for the storage of detailed data. The suggested potential information to store was: country of registration, chemical type, unique registration number of an agrochemical, container size, specific gravity, unit of measure and a digital signature addressing the data integrity and security.

University of Georgia Precision Agricultural Team developed a wireless sensor networks for scheduling irrigation in cotton (Vellidis et al., 2007). The soil moisture and temperature was monitored using this network system. This network consisted of a receiver, laptop computer, and sensor nodes installed in the field. Each sensor node consisted of up to three moisture sensors and four thermocouples. In each node, a RFID tag transmitted data to the receiver through a specially designed circuit board. This wireless sensor network system was able to provide real time information regarding the geospatially variable soil water status in cotton field, which can be used for a closed loop irrigation control system to determine timing and amounts for real time site-specific irrigation application.

9.3. Future perspectives

Although the development of the RFID is fast, there are several technical challenges that prevent it from being widely adopted in the industry. The first issue is its high cost. An average RFID costs roughly 20–30 cents apiece, which is too costly for some products with only 50 cents value such as fruits and vegetables. Second, RFID signals are relatively weak and can be attenuated or blocked over short ranges by certain material. Third, there is no standard for this technology currently, which causes the incompatibility of tags and readers in some cases.

Compared to the Universal Product Code (UPC) bar codes which are read optically at very short distances, the RFID tags can be read at much longer distances through radio waves and can also store much more information than mere an ID code in the product. For instance, besides the ID number for each produce, the RFID tags can store the origins and the growing information about the produce. It is foreseeable that the RFID systems will replace the Universal Product Code (UPC) bar codes in the near future. Some experts predict that RFID will be widely used around 2015, when the cost of RFID tags falls enough to make them economically viable for labeling inexpensive consumer products (Want, 2003).

In summary, the RFID technology makes it possible to monitor and observe the physical world in ways not previously possible. They will greatly enhance the productivity of specialty crops production and postharvest operations.

10. Machine olfaction system

The sense of smell is one of the most important senses for humans and animals. Humans can recognize approximately 10,000 scents and many animals, such as bloodhounds, even have far superior olfactory system than humans (Axel, 1995). Olfaction enables most animals to identify food, predators and mates with both sensual pleasure and warning of danger, which is essential for their survival (Leffingwell, 2002). The human perception of certain odors can induce specific thoughts, memories, and behaviours, as well as help us identify whether a food is editable or not.

Many studies have proven that compositional changes in volatiles occur during fruit and vegetable ripening, and vary depending on the presence of diseases and physical damages (Hirvi and Honkanen, 1983). By detecting these volatile changes, the physical properties and quality of fruits and vegetables can be evaluated. Trained human panelists are usually used for applications ranging from food quality inspection, perfumes and cosmetics aroma

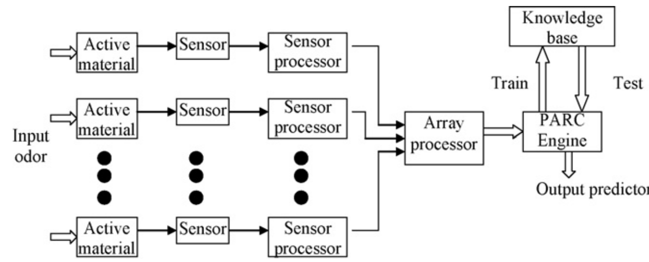


Fig. 9. A generic electronic sensor architecture (adapted from Gardner and Bartlett, 1994).

evaluation, to agricultural product odor detection. However, the main drawback of human sensory panels is that they cannot detect volatile compounds without odor, while many such compounds are very important indicators for agricultural produce quality. Humans are also subjective and can only work for a short period of time. Analytical equipment such as gas chromatography-mass spectrometry (GC-MS) are effective in detecting constituents in volatile mixtures, but they are expensive, time consuming, and sometimes not adequate (Gardner and Bartlett, 1994).

The development of the electronic nose seems to address these issues. In the early 1980s, Persaud and Dodd (1982) at Warwick University developed a prototype of electronic nose as an intelligent chemical sensor array system to classify odors. Since then, the development of the electronic nose has been growing rapidly and many conferences were held on this topic (Gardner and Bartlett, 1994). The electronic nose is also called an artificial nose or mechanical nose: "An electronic nose is an instrument which comprises an array of electronic chemical sensors with partial specificity and an appropriate pattern-recognition system, capable of recognizing simple or complex odors".

A generic architecture of an electronic nose was proposed by Gardner and Bartlett (1994) as shown in Fig. 9: an odor reacts with the sensor array which converts the chemical reaction into an electrical signal. Further data processing and classification is made by a pattern recognition (PARC) engine.

The term "electronic nose" has been admitted by many researchers because it possesses two basic characteristics of the human olfactory system: first, the electronic nose gas sensors and pattern recognition software are conceptually analogous to human olfactory receptors and the brain, respectively; second, the electronic nose recognizes the odor by an overall smell pattern instead of identifying each different constituent of an odor, which is similar to the human smell principle. Nevertheless, the electronic nose does not work in the same way as the human nose does, and its sensitivity is still far less powerful than the human nose (Mielle, 1996).

10.1. The electronic nose system

The electronic nose system typically consists of two major components: hardware (gas sensors) and software (pattern recognition program). A gas sensor is a device that responds to a wide range of volatile molecules in gases and is capable of converting a chemical quantity into an electrical signal. Typically, the gas sensors are based on different principles including electrical, optical and mass change. Generally, the commercial electronic noses can be divided into two categories based on their working temperature: hot sensors which operate at elevated temperature (100–500 °C) and cold sensors which work at ambient temperature (Mielle, 1996). An ideal gas sensor should possess the following characteristics (Mandelis and Christofides, 1993; Schaller et al., 1998):

a. High sensitivity to chemical compounds of interest and low sensitivity to humidity
b. Chemically selective: they must respond differently to different volatiles
c. Reversible
d. Non-contaminating and non-poisoning
e. Short reaction and recovery time
f. Robust and durable
g. Easy calibration
h. Simple operation
i. Small dimension
j. Low noise and low cost

10.2. Metal oxide semiconductor gas sensors

Metal oxide semiconductor gas sensors (MOS), which were invented by Taguchi in 1960s, are one of the earliest commercially available gas sensors with more than 70 types and many providers (Schaller et al., 1998). Basically, MOS gas sensors detect the conductivity change caused by the adsorption of gases and subsequent surface reactions. There are two types of MOS gas sensors based on the metal oxide coating film: n-type semiconductors which are composed of zinc, tin or iron oxide and respond to reducing compounds; p-type semiconductors which are composed of nickel oxide or cobalt oxide and respond to oxidizing compounds such as O_2, NO_2 and Cl_2 (Mielle, 1996).

The working mechanism of MOS gas sensors follows two steps: first, oxygen from air is adsorbed on the surface of metal oxide semiconducting film and oxygen traps free electrons from the semiconductor, which increases the resistance of the semiconductor; second, the electrons are freed by means of reaction of the oxygen and reducing gas, which reduces the resistance of the semiconductor. Hence, the presence of the reducing compounds at the surface of the semiconducting film increases the conductance in a nonlinear manner (Schaller et al., 1998; Pearce et al., 2003). The selectivity of a metal oxide film to different chemical compounds can be modified by doping with different catalytic metals, and changing the working temperature within a range of 50–400 °C (Sberveglieri, 1992). Due to its high working temperature, MOS gas sensors are insensitive to humidity and usually can be used for a longer time (5 years) than other gas sensors, such as conducting polymer sensors. However, the main weaknesses of MOS gas sensors include that they are extremely sensitive to ethanol which may blind the sensor to detect other compounds, that they may be poisoned by irreversible binding by compounds such as sulfur compounds or weak acids such as vinegar and cheeses, and that their high working temperature prevents them from being used in an environment containing large amounts of flammable chemicals (Mielle, 1996).

MOS gas sensors can be manufactured in a large scale, which guarantees repeatability between different sensors and reduces the sensor costs. The main providers for this gas sensor include Figaro Engineering Inc. and New Cosmos Electric Co., Ltd (Pearce et al., 2003).

10.3. Conducting polymer gas sensors

The conducting polymer gas sensor is another widely used and commercially available gas sensor. Similar to the MOS gas sensor, the conducting polymer gas sensor also identifies odors by detecting sensor resistance change, although its operating mechanisms are more complex and have not been well understood so far (Mielle, 1996).

Basically, these types of sensors are made of three main components: a substrate, a pair of gold-plated electrodes, and a conducting organic polymer layer. When the sensor is exposed to an analyte, the conducting organic polymer film swells, which causes the increase in resistance because the conductive pathways through the material are disrupted. Typically, this type of sensor consists of a sensor array, and each sensor can respond to a variety of vapors with partial overlapped selectivity. An array of sensors which contain different polymers produces a distinct fingerprint for each odor, due to their different swelling properties. The pattern of the resistance change over the sensor array provides the evidence for qualitative classification of different smell patterns, and the amplitude of resistance change gives quantitative evidence for vapor concentration (Sberveglieri, 1992).

Polymers are relatively cheap and a large number of polymers with different functions are available, which can be used to fabricate different selective sensors. Commonly used polymers include polypyrroles, polyanilines, and polythiophene (Schaller et al., 1998). Another main advantage of using conducting polymer sensors is that they can be operated in ambient room temperature. However, their relatively slow response (20–40 s) and drift over time are inherent drawbacks which prevent them from being used for rapid analysis and obtaining repeatable results over long periods of time. One main provider of CP gas sensors is Smith Detection (Smith Detection Inc., CA) which produces the Cyranose 320 electronic nose.

10.4. Surface acoustic wave (SAW) sensors

A surface acoustic wave sensor detects volatile compounds by sensing the mass change based on a piezoelectric effect. Piezoelectric crystals have a very stable resonance radiofrequency which propagates on the surface of the crystal. The radiofrequency oscillation in SAW, known as "Rayleigh waves", is adjusted by the mass change due to the presence of adsorbed volatile compounds (Sberveglieri, 1992). Usually, the characteristic frequency is in the range of 100–1000 MHz. The piezoelectric materials are made of ZnO or lithium niobate and they are coved by two pairs of interdigitated combs which are typically made of aluminum and used as wave emitters and reflectors. The sensing membrane can be chemically modified to adjust the sensor's specificity. The frequency change Δf_V of the SAW due to the adsorption of vapor and consequent mass change can be expressed as (Pearce et al., 2003):

$$\Delta f_V = \frac{\Delta f_p c_V K_p}{\rho_p} \tag{2}$$

where Δf_p is the change in frequency caused by the polymer membrane itself, c_V is the vapor concentration, K_p is the partition coefficient and ρ_p is the density of the polymer membrane.

SAW sensors are highly sensitive but noise caused by analogue electronics easily interferes with them. Other drawbacks include the difficulty to replace sensors and a drift of response due to temperature fluctuations (Mielle, 1996).

10.5. Optical gas sensors and others

Optical gas sensors detect odors by sensing the optical properties such as absorbance, reflectance, fluorescence or chemiluminescence when a light source excites the gas. A typical optical gas sensor consists of four components (Pearce et al., 2003): a light source, suitable optics, a detector and the sensor. For instance, at one end of the fiber, an analyte-sensing element is deposited on fibers with a diameter of 2 μm and imaging bundles with a diameter of 500 μm. Analyte gases can interact with the sensing element and generate optical property changes such as intensity change, spectrum change, and wavelength shift in fluorescence. These changes can be detected at the other end of the fiber and the responses reflect not only the nature of the vapor mixture but the concentration of gases (White et al., 1996).

Optical gas sensors have advantages such as being free from electromagnetic interference, extremely low light attenuation, and very high sensitivity (for fluorescence). However, they are also more expensive, more complex, and sometimes suffer from photodegradation on their fluorescent indicators (White et al., 1996). Although they have not been commercialized, optical gas sensors are being actively researched and they are gaining much publicity. An example is Tufts University's optical electronic nose, notable for the biological inspirations behind the sensors (Dickinson et al., 1996). Other research on surface plasmon resonance (SPR) and colorimeter coupled optical fibers is also underway (Ballantine et al., 1992; Nelson et al., 1996).

There are many other efforts to make artificial noses based on different principles, enhancing their capability to mimic a human nose. For instance, an electronic nose was made to differentiate fruit cultivars by utilizing only 1 s odor sniffing samples, and it achieved encouraging results (Gelperin et al., 1999; Ouellette, 1999). Researchers also tried to combine biotechnology (single stranded DNA) and nanotechnology (single wall nanotube) to develop new generation of artificial noses (Staii et al., 2005), which may open a new door for gas sensing technology.

10.6. Pattern recognition algorithms

Essentially, the machine olfactory system is a combination of chemical sensors and a pattern recognition system that can discriminate different odor patterns. Thus, the pattern recognition is indispensable in a machine olfaction system. The electronic nose typically consists of an array of sensors and thus the data from the electronic nose is multivariate in nature. The multivariate statistical data analysis techniques are usually used to process the electronic nose data. These techniques include principal component analysis (PCA), multivariate analysis of variance (MANOVA), cluster analysis (CA), and discriminant analysis (DA). The artificial neural networks (ANN) often give higher recognition and prediction probability than statistical classification algorithms. Another classification algorithms, support vector machine (SVM), gains more popularity in recent years due to better performance and ease of use (Hsu et al., 2007).

10.6.1. Principal component analysis

The principal component analysis (PCA) is one of the most useful techniques for multivariate data analysis, which is based on Karhunen-Loeve expansion and used to reduce the dimension of the problem by projecting the data from a p-dimensional space to a k-dimensional space ($k < p$) (Anderson, 2003). It is used for reducing the dimensionality of the data while preserving the structure. PCA uses eigenvectors and eigenvalues to define the reduced subspace, which is a representation of the original p-dimension space. The principal components are linear combinations of interrelated variables. Coefficients of the linear combinations are the eigenvectors of the covariance or correlation matrix. A correlation matrix was used in this analysis to enhance the influence of small spectral features. The PCA score plot can provide information on the clustering of data, while the PCA loading plot can be used to investigate the contribution from each sensor.

10.6.2. Bayesian discriminant analysis

Both the linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA) are based on Bayesian discriminant theory (Anderson, 2003). In Bayesian discriminant analysis, the *prior* probability is defined as the probability of a random sample belonging to population π_i:

$$p_i = Pr(\pi_i) \tag{3}$$

We assume that the observations X from population π_i is sampled from a multivariate normal distribution with mean vector μ_i and variance–covariance matrix Σ_i.

The *posterior* probability that a random sample belongs to population π_i is:

$$p(\pi_i) = \frac{f(x/\pi_i)p_i}{\sum_{j=1}^{g} f(x/\pi_i)p_j} \tag{4}$$

The decision rule is to classify the sample unit into the population π_i that maximizes the posterior probability $p(\pi_i)$.

10.6.3. Artificial neural networks

Gas sensor array data may often be non-linear in nature, and artificial neural networks as a non-linear method could provide a more robust classification model. Inspired by biological nervous system, the neural networks are composed of simple elements operating in parallel. By adjusting the weights (connections) between elements, a neural network can perform a particular function (Bishop, 1995). Commonly, neural networks are adjusted, trained by the training data set in which the specific target value is known. After a neural network is trained, it can be applied to classified unknown data set.

The backpropagation (BP) network is known for its ability to generalize well on a wide range of problems. This network is generally robust, although one drawback is that the training is slow. Typically, three layers (input, hidden, and output layer) are sufficient for the vast majority of problems and each layer is connected to the immediately previous layer.

The probabilistic neural network (PNN) can be trained quickly on sparse data sets. PNN networks are three layer networks wherein the training patterns are presented to the input layer and the second layer produce a vector of probabilities. The output layer picks the maximum of these probabilities and produces a 1 for the class and a 0 for the other classes. PNN uses the radial basis function in its second layer.

The learning vector quantification network (LVQ) is a supervised competitive ANN which transforms high dimensional data to a two-dimensional grid, without regarding data topology. LVQ uses pre-assigned cluster labels to data items to facilitate the two-dimensional transformation so as to minimize the average expected misclassification probability. LVQ usually has the slower training speed.

10.6.4. Support vector machine

Support vector machine was proposed in the later seventies (Vapnik, 1995) and now receiving increasing attention due to its good generalization performance. It is a supervised learning method used for classification and regression. The basic idea of the support vector machine is that it simultaneously minimizes the empirical classification error and maximizes the geometric margin between two data sets. Support vector machine has been used in the electronic nose data analysis (Distante et al., 2003). In one case, it was used to create a prediction model to classify lung diseases (Machado et al., 2005).

10.7. Application of volatile-sensing sensors in specialty crops

Most fruits have distinct aromas and their volatile profile changes when they become ripening or with the disease's presence. There are three major reasons for the volatile profile changes: metabolic changes, interaction with the environment, and possibility of infections. By utilizing this special characteristic, the electronic nose has been successfully applied in fruit ripening prediction and quality measurement.

A metal oxide semiconductor (MOS) based electronic nose was used to classify four peach cultivars and to assess the ripening stage during the shelf-life (Benedettia et al., 2008). An electronic nose based on metallopophyrin-coated quartz microbalance sensors was used to classify tomatoes grown in the conventional and organic production systems (Sinesio et al., 2000). The enose result was compared with the trained human sensory panel. A tin oxide chemical sensor array and neural network was applied to classify peaches, pears and apples into three different stages of ripeness. The electronic nose showed 92% success rate for peaches and pears, and a slightly lower accuracy for apples (Brezmes et al., 2000). Marrazzo et al. (2005a) studied the feasibility of using the prototype electronic nose which consists of 32 conducting polymer chemical sensors, to compare 'Malus domestica Borkh' apple headspace gas. Apple headspace volatile chemicals were measured in terms of apple flavors, essences, and known component mixtures by the e-nose and the results were assessed according to change over time, between cultivars, and between whole apple and juice from the same apple (Marrazzo et al., 2005a,b).

Oshita et al. (2000) applied the semi-conducting polymer based electronic nose to measure the odors emitted from 'La France' pears which were treated in three different storage conditions after being harvested. It was found that the electronic nose was able to classify pears into three classes dependent on their physiological states through distinctive odor pattern formed by 32 outputs. A strong relationship between the results obtained by headspace GC and the electronic nose was observed. Brezmes et al. (2001) used an electronic nose to evaluate the ripeness of pinklady apples. Fruit quality indicators were also obtained by a chemical analysis approach to compare results from both techniques. Among them, firmness was the best-predicted parameter with a correlation coefficient of 0.93.

It is important to monitor and control the variations occurring during fresh fruits postharvest period. A thickness shear mode quartz resonator (TSMR) based electronic nose was used to detect the presence of mealiness and skin damage of apples and oranges (Di Natale et al., 2001). It was found that the electronic nose was more sensitive to the presence of surface damages than to the mealiness.

The electronic nose can be used to monitor the ripeness of fruits and help determine the harvesting time. Saevels et al. (2003) applied an e-nose as a non-destructive tool to evaluate the optimal harvest date of apples. Calibration models for the prediction of the maturity had a validation correlation of 0.91 for 'Jonagold' and 0.84 for 'Braeburn'. Four apple quality characteristics (soluble solids, acidity, starch and firmness) were predicted by calibration models, which were based on two years data for two cultivars. Use of the e-nose as a non-destructive approach to predict the optimal harvest time of apples is valid, however, the measurement time is too long to be a fast technique.

Usually more sources of data provide more information and achieve better performance. Multi-sensor data fusion approach combines data from multiple sensors and gets a better interpretation of the target than using individual sensor alone (Hall, 1997). The multisensor data fusion models were developed to combine the Cyranose C320 electronic nose and the zNose to detect defective apples (Li et al., 2007). A benchmark study was conducted to compare three artificial neural networks for their classification performance (Li and Heinemann, 2007). The genetic algorithms were applied to optimize the feature selection and reduce the data dimensionality (Li et al., 2008). At the feature level fusion, ANN-based fusion models reduced the classification error rate to 1.8% on average in 30 independent runs, and at the same time only about 50% of the sensors from the Enose and zNose were used for input. At the decision level fusion, a Bayesian network was developed to integrate classification decisions made by the Enose and zNose classifiers independently. Sensor fusion models were validated by testing on new data sets and achieved 81% and 82% classification accuracy at the feature level and decision level, respectively (Li et al., 2007).

Pathogenic contamination of fruit is a dangerous threat to human health and there are currently no instruments to detect these contaminations on the surface of fruits on site. The electronic nose has also been used for fruit pathogen detection. Powell et al. (2002) conducted preliminary research of detecting *E.coli* on the surface of 'red delicious apple'. The e-nose was exposed to the air samples of contaminated and non-contaminated apples and different sensor responses were assessed. Their results showed that some sensors had strong responses to the air samples at two dilution rates. They suggested that further research should be conducted to clearly define separation between the dilution rates in order to identify the presence of the *E. coli* and its concentration on apples.

10.8. Future perspectives

The electronic nose has shown great promise in specialty crop quality and safety measurement. However, it is still widely regarded as in its early development stage. As the advancement of the instrument hardware and software, the electronic nose technology is expected to have a better selectivity, sensitivity and repeatability as envisioned below.

(1) The calibration method needs to be designed for the electronic nose in order to counter the sensor drift effect and generate repeatable results. This goal can be achieved by developing mathematical algorithms for drift counteraction and automatic calibration.
(2) New gas sensor technology development is expected to take place in the next decade, such as fiber-optic based sensors, carbon nano tube based gas sensors, and insect-based gas sensors (Rains et al., 2006). The ideal gas sensor is expected to have a higher sensitivity and better stability.
(3) The future electronic nose should have a broader sensor array like our human olfaction receptors which enables a stronger odor discrimination power. However, sometimes this broad selectivity is not needed in certain applications, and the sensor selection is needed to reduce the data dimensionality.

There is still a long way to go before the electronic nose can be fully automated in the specialty crops industry. In the near future, it is foreseeable that more on-line gas-sensors will be implemented in the industry. The electronic nose will be an important component in a multi-sensor system to characterise the quality of fruits and vegetables.

11. Conclusions

In this study, many different sensing technologies for specialty crop production utilizing precision agriculture have been reviewed. Based on the observations and recommendations from these studies, the following needs and future directions have been identified.

Commercial yield monitors are currently available for major crops such as grain and cotton, but there are no commercial yield monitors for most specialty crops. While accurate estimates of yield are not always possible during the growing season, yield patterns and within-field management zones identified from airborne multispectral and hyperspectral imagery can be very useful for both within-season and after-season management. Substantial research on remote sensing for yield estimation is needed in order to adapt the existing methods and develop new methods for specialty crops. Robotic harvesting still poses a great challenge. Improved fruit detection algorithms are needed for both yield estimation and coordination of robotic arms for harvesting.

Computer vision is being extensively used as the primary sensor for different tasks in precision agriculture. Although sensing technology has advanced a lot, still the completed tasks are simple. This is due to the complex and unstructured nature of the agricultural environment. Recent research has shown that the use of task-specific wavelengths in the visible and beyond the visible spectrum range increases the number of successfully accomplished tasks. Nevertheless, color machine vision is the most common form of machine vision that is used today because it is driven by commercial forces in other fields than agriculture, such as consumer photography and video.

More research is needed in the field of processing methods in hyperspectral imaging. Furthermore, recent research shows that there is a great potential for fusion of several image sources. In order for such systems to become more accessible and available, more study is needed in the field of automatic image co-registration, development of models that take into account different properties of the inspected objects and makes clever interpretation of the fusion between the images.

In the field of water status mapping, although thermal IR imaging becomes increasingly available, there is a great need towards the development of acquisition and processing techniques that exploit the advantage of the high accuracy of thermography on one hand, and can compensate for the relatively low spatial resolution of the cameras on the other hand.

Wireless sensor networks have been developed, however much improvement is still needed in various aspects of the technology such as communication range and availability of radio frequencies. Sensor networks are basically depending on individual sensors, however only a limited number of sensors are currently available for specialty crop production. Technological advances and synergistic effect in both sensors and wireless communication will be needed to enhance the performance of sensor networks.

There have been limited sensing techniques for variable rate chemical application to specialty crops. There is a need for developing an easy-to-use and low cost commercial unit so that the growers could adopt them without too many difficulties.

Sensing systems for soil properties and nutrients have been developed and some of them have been implemented for real-time variable rate nutrient applications. However, due to the large variations in soil properties, many studies suggested site-specific calibrations of soil sensors. It remains as a challenge the automatic mapping of soil properties over large geographic areas without intensive calibrations. It would be better if there was a new technique that could accommodate the spatial variabilities of soil properties for real-time applications. Developing global soil spectral libraries could be an example.

The underlying mechanisms for noncontact detection of foliar diseases in crops were discussed including sensing techniques and main biological phenomena caused by a disease infestation. Most diseases can be detected more easily when they are fully developed. Combinations of spectral changes at different infection stages are recommended for more efficient foliar disease detection.

Many crop diseases have been identified as good candidates for remote sensing, but practical procedures for farming operations are still lacking. Efforts need to be devoted to the development of operational methodologies for detecting and mapping these candidate diseases. Meanwhile, more research is needed to evaluate more advanced imaging systems, image processing techniques and advanced classification algorithms combined with sensor fusion techniques for distinguishing the diseases that are difficult to detect or occur simultaneously with other stresses.

RFID technology has been studied for tracking agrochemicals and irrigation sensor node information. Due to high cost, weak signal, and lack of standard, its applications have been limited, however are expected to be expanded in the near future. The electronic nose has shown potential in specialty crop application, however needs further development for a better selectivity, sensitivity and repeatability.

Although many of the technologies of precision agriculture are relatively mature (i.e., GPS, GIS, and satellite or airborne remote sensing), there remains ample room for improvement. One of the most important is the development of local or proximal sensors that can be used on farm equipment to determine crop stage, soil conditions and chemistry, weed concentrations, presence of insects, and other risk factors important for crop growth.

Another problem is how to determine optimal sampling strategies. Some precision agriculture technologies function by adjusting farming practices (i.e., nutrient application rates) to match variability in soil nutrient levels or other factors. The knowledge of the extent of variability is essential at all spatial levels.

The development of standards for hardware, software, and data interpretation can influence the development and the adoption of precision agriculture. From the perspective of the user, standardization would facilitate easier data interchange, particularly moving spatial data from one proprietary software package to another and to regional databases. Standards affecting data and hardware interchange affect the integration and ease of using these new technologies. Precision agriculture is technically possible today, but requires a high degree of technical know-how and persistence from the end-user.

Overall, more reliable, accurate, rugged and less expensive sensing systems in different aspects of crop production will be needed for better and efficient site-specific management of specialty crops. Even though crop and field conditions are highly variable thus complicating certain sensing tasks, the future is promising as there are many researchers who continue to have interests in sensing systems and concentrate their efforts on technological advances.

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